DEVELOPMENT OF A PAVEMENT MAINTENANCE AND REHABILITATION PROJECT FORMATION AND PRIORITIZATION METHODOLOGY THAT REFLECTS AGENCY PRIORITIES AND IMPROVES NETWORK CONDITION

A Thesis

by

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ABSTRACT

Methodical maintenance and renewal of infrastructure systems is critical due to the rapid deterioration of infrastructure assets under increasing loads and environmental effects and the scarcity of resources allocated for their preservation. A crucial step in pavement management is the formation and prioritization of maintenance and rehabilitation (M&R) projects that compete for limited funding for inclusion in the agency's multi-year pavement management plan (PMPs). In general, many highway agencies perform this task subjectively, and thus a more rational and objective approach is desired to produce sound and justifiable PMPs. Specifically, such methodology should take into account the multiple factors that are considered by engineers in prioritizing M&R projects. This research addresses this need by developing a methodology for use by the Texas Department of Transportation (TxDOT) in preparing their four-year PMPs.

Several key decision factors were considered and TxDOT decision makers were surveyed to weigh these factors as to their influence on prioritizing M&R projects. These were then used to develop a priority score for each candidate M&R project.

Since TxDOT collects and stores data for individual 0.5-mile pavement sections, these sections must be grouped in a logical scheme to form realistic candidate M&R projects. The incremental benefit-cost analysis was performed on the candidate M&R projects to identify a set of M&R projects that maximizes network's priority score under budgetary constraint. Future pavement condition was projected using performance

prediction models and the process is repeated throughout the planning horizon to produce a multi-year pavement management plan.

Data from Bryan district, which consists of 7,075 lane-miles of roadway, were used to develop and validate the PMP methodology. Comparison with the actual PMP (produced by TxDOT) shows some disagreements with the PMP generated by the methodology though the latter was shown to produce more cost-effective and defendable pavement management plans. Since the methodology is founded on TxDOT engineers' decision criteria and preferences, they can be assured that the PMPs produced by this methodology are in line with their goals and priorities.

DEDICATION

In memory of Lolo Ambo and Lola Miling

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NOMENCLATURE

AADT	Annual Average Daily Traffic
AHP	Analytic Hierarchy Process
AUPC	Area Under the Performance Curve
CDA	Cumulative Difference Algorithm
CS	Condition Score
DS	Distress Score
HR	Heavy Rehabilitation
IBC	Incremental Benefit-Cost
LCC	Life-Cycle Cost
LR	Light Rehabilitation
LTPB	Long-Term Performance Benefit
M&R	Maintenance and Rehabilitation
MR	Medium Rehabilitation
PDA	Proximity to Deficient Areas
PM	Preventive Maintenance
PMIS	Pavement Management Information System
PMP	Pavement Management Plan
RS	Ride Score
TxDOT	Texas Department of Transportation

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1. INTRODUCTION

1.1 Background

Faced by rapidly deteriorating road infrastructure and stringent budget conditions, road managers are beset with the problem of how to prudently spend scarce resources to preserve their assets. To carry out this task, road agencies are equipped with Pavement Management Systems (PMS) that provide useful information and analytical tools so that Maintenance and Rehabilitation (M&R) decisions are made in an objective, cost-effective, and justifiable manner (Finn et al. 1990). M&R decisions involve identifying, prioritizing, and planning of M&R activities so that an acceptable level-of-serviceability is attained. A PMS supports these decisions by determining the funding necessary to meet network goals (called needs estimation) as well as analyzing the consequences of having limited funding on network condition (called impact analysis) (Stampley et al. 1995).

In general, infrastructure management functions in most large highway agencies are organized in three levels: central, district, and field. The central or head office level of management is responsible for establishing network goals and developing overall M&R strategies to help meet these targets. The districts have the responsibility of determining M&R priorities over their areas of supervision that are in line with agency goals. The field level of management is responsible for monitoring and correcting localized deficiencies through on-site inspection and execution of M&R projects (Haas and Hudson 1978). These concepts are demonstrated in the case of the Texas

Department of Transportation (TxDOT) whose pavement management data and processes are the subject of this research study.

TxDOT is responsible for the upkeep of more than 195,000 lane-miles of roadway in the state of Texas. Like other transportation agencies, it is also experiencing the same trends in pavement condition and funding limitations. For instance, a 2011 report (Peddibhotla et al. 2011) predicted that using TxDOT funding projection for the years 2010 to 2035, pavement condition will gradually decline while funding will continue to be limited due to factors like escalation of construction cost and reduced fuel tax revenue. To further heighten the challenge for TxDOT, the Texas Transportation Commission in 2002 set a statewide goal of having 90% of the state-maintained pavement lane-miles in "Good" or better condition by 2012. Thus, TxDOT needs the right tools to support its operations if it is to surmount these challenges. At present, TxDOT uses its Pavement Management Information System (PMIS) primarily to obtain valuable data on pavement condition, and to a much lesser extent as an analytical tool that can assist decision makers in developing strategies for evaluating, maintaining, and rehabilitating pavements in acceptable condition.

Pavement management functions in TxDOT basically follow the general organizational structure described previously. Every year, TxDOT staff and consultants rate all pavements through visual inspections and automated measurements (Zhang et al. 2009). The ratings are then stored in PMIS from which preliminary candidate projects for M&R are identified by some districts. Each of the 25 districts of TxDOT then prepares their own four-year Pavement Management Plan (PMP) by ranking the projects using various prioritization techniques and evaluation indexes. Generally, the PMP is a living document where projects are re-evaluated and reprioritized every year for the following four years. Lastly, the plans, and each district's needs estimate are combined and submitted by TxDOT to the legislative budget board and to the governor to describe how the districts intend to use their pavement management funds (Zhang et al. 2009). In light of this process, it is obvious that PMPs must be prepared in a systematic and justifiable manner.

The specific task of prioritizing M&R projects at the district level is the main subject of this research. While some continue to perform this task subjectively by relying on the engineers' experience, this approach may not yield optimum pavement management plans and may be difficult to defend (Gurganus 2011). On the other hand, a more objective approach is to take into account a variety of key factors that reflect the decision makers' priorities in the decision making process. Hence, this research seeks to improve current pavement management planning practices by developing a methodology that will objectively and cost-effectively prioritize competing M&R projects at the district level.

1.2 Problem Statement

Highway agencies develop pavement management plans that identify candidate M&R projects over multiple years into the future. In Texas, each district of TxDOT is required to develop a four-year pavement management plan. Currently, varying forms of ranking indices, priority weights, and prioritization methods are used to identify candidate M&R

projects for these plans. The conjuncture of this thesis is that a structured methodology for prioritizing pavement M&R projects is more advantageous than the current ad-hoc approach for generating PMPs because:

- It enables the highway agency to automate the computational components of the PMP development process; allowing the engineers to focus on defining and understanding the decision criteria.
- It enables the engineers to perform sensitivity analysis to understand how and how much different inputs (e.g., priority weights) influence the outputs (e.g., selected projects and network condition).
- It enables the highway agency to justify project prioritization decisions by clearly explaining the methodology used to arrive at these decisions.
- It provides inexperienced engineers with a decision support tool that reflects the decision making process within their organization.
- It brings consistency among the various districts within the highway agency in terms of the process used for generating PMPs. While the districts might differ in terms of the decision criteria, they would use the same analysis method.

Developing this methodology involves addressing the following research questions, which will be addressed in this research as they apply to TxDOT:

(1) What project formation scheme can be adopted to improve the formation of candidate M&R projects?

(2) What are the key decision factors that TxDOT districts consider in prioritizing M&R projects and what weights do TxDOT decision makers assign to each factor?

(3) How can multiple decision criteria be incorporated in the project prioritization methodology?

(4) How well does the developed methodology match actual district pavement management plans?

TxDOT's PMIS divides the roadway network into data collection sections (typically 0.5-mi long) and stores data for each one of these pavement sections. Consequently, the needs assessment tool also evaluates pavements based on these data collection sections. In contrast, M&R works are neither contracted nor performed on individual 0.5-mi sections but on projects that usually stretch for two miles or longer. Thus, a project formation scheme must first be devised and applied to form realistic projects out of 0.5-mile sections of approximately similar M&R needs.

The PMIS contains a needs assessment tool which is intended to assist the districts in identifying road sections that need M&R action. This tool, however, does not prioritize projects when funding is limited (Dessouky et al. 2011). Furthermore, Gurganus (2011) discovered discrepancies between preservation actions recommended by the PMIS and actual M&R projects implemented. Based on interviews, it was found that most districts use PMIS as a mere depository of pavement data and that PMIS's needs assessment tool plays a limited role in helping the districts in the project selection process. This led to a conclusion that the needs assessment tool does not completely account for all factors that influence pavement M&R decisions (Gurganus 2011). Thus, improving this tool will indeed warrant a deeper look at the key factors that the districts consider in making M&R decisions. Also, it is important to obtain representative importance weights for these decision factors. In addition, this will help determine whether the districts prioritize their M&R projects according to a worst-first approach or a long-term strategy.

Considering multiple decision criteria poses the problem of factors being expressed in different units of measurement and therefore cannot be readily compared or aggregated. Hence, a prioritization index that combines all factors into a single metric will be useful in selecting the optimum set of M&R projects that maximizes benefit under budgetary constraints.

Finally, determining how well the developed pavement management plans match with actual plans will validate the soundness and practicality of the developed PMP methodology.

1.3 Research Objective

The aim of this research is to develop a sound and justifiable decision support methodology that TxDOT can use to prioritize pavement M&R projects and generate defendable PMPs. The specific objectives of this research are to:

(1) devise a scheme for forming realistic M&R projects out of data collection sections that are typically 0.5-mile long;

(2) identify the key factors that influence M&R project prioritization decisions at the district level and elicit representative weights for these decision factors based on a survey of TxDOT districts;

(3) develop a multi-criteria project priority index for use in the optimal selection of candidate M&R projects;

(4) integrate the developed project formation scheme, multi-criteria project priority index, and benefit-cost analysis to create a methodology for prioritizing pavement M&R projects and generating PMPs; and

(5) validate the developed methodology through comparisons to actual district pavement management plans.

1.4 Research Tasks

To accomplish the objectives of this research, the following tasks were completed.

- Task 1: Review of Related Literature

  Literature on pavement M&R prioritization and planning was reviewed to identify key decision factors commonly used in project prioritization and to understand the rationale for their inclusion in the process. Studies dealing with multi-criteria decision making and optimization in infrastructure management were also given specific attention. To design a methodology that best suits TxDOT practices, TxDOT manuals and completed research reports were also reviewed.

- Task 2: Devise a Project Formation Scheme to Form M&R Projects out of Short Data Collection Sections

  The Cumulative Differences Algorithm (CDA) was applied to divide the network into segments that are homogeneous with respect to several attributes and having approximately uniform M&R needs. This technique however, tends to obscure localized poor-condition pavements and overlooks them in the analysis. Thus, an alternative scheme that addresses this drawback was developed.

- Task 3: Survey TxDOT Districts to Obtain Weights of Decision Factors

  A web-based survey was developed and disseminated to TxDOT's 25 districts to obtain weights for the key factors identified as influential in identifying and prioritizing pavement M&R activities. This was done according to the Analytic Hierarchy Process (AHP) where the factors' relative weights are computed based on pairwise comparisons of the factors considered (Saaty 1980).

  The weights obtained are to be used to gauge the respondents' propensities when prioritizing pavement M&R projects. This is done for all responses, representing state-wide weights, and separately for metropolitan, urban, and rural districts. The weights obtained from this survey are used as default values in the developed project prioritization methodology.

- Task 4: Develop a Prioritization Methodology for Pavement M&R Projects

  The prioritization methodology was designed to meet the following considerations: (1) it uses existing data available in the PMIS and other attribute data that can be provided directly by the districts; (2) prioritization must be made on formed roadway segments that represent realistic M&R projects, and not on 0.5-mi data collection sections; (3) multiple decision criteria must be incorporated in the prioritization process; (4) it must have the capability of prioritizing projects to maximize the benefits or cost-effectiveness for the network; (5) it must be able to project future pavement condition using performance prediction models; and (6) results must be reported in a clear and logical manner.

- Task 5: Validate Methodology

  The four-year PMP produced by the methodology is compared with that of the actual PMP of Bryan district. The following matters are evaluated to validate the practicality and soundness of the methodology: (1) agreement in the four-year needs estimate; (2) agreement of the formed pavement segments with actual M&R project boundaries; and (3) the impact of the methodology's PMP on network condition vis-à-vis the impact of the actual PMP. Disparities between the developed PMP and Bryan district PMP are discussed.

1.5 Thesis Organization

This thesis is divided into eight sections as described in the following paragraphs.

Section 1 provides a general background of the research topic and states the problem that it aims to address. Specific objectives are enumerated and the research approach used to meet these objectives is outlined.

Section 2 reviews existing literature on various topics that are covered in this research. It discusses past and current research efforts on areas such as multi-criteria decision making, roadway segmentation, and optimization in infrastructure management at the network level.

Section 3 discusses the first part of the prioritization methodology, which is the grouping of data collection sections to form project segments. Two project formation schemes are discussed and compared with each other. The incorporation of user-defined assessments of pavement condition and forced M&R projects are also presented.

Section 4 discusses the key factors considered in the multi-criteria prioritization methodology developed. It provides a detailed description of each criterion and the rationale for their use. The mechanics of the web-based survey and the details of the procedures of the AHP that was used to obtain priority weights are also presented. The calculation of the weights is shown and the survey results are analyzed.

Section 5 provides an overview of the methodology. It discusses the performance prediction models developed, and how they are used in the project prioritization methodology. This section also illustrates how each candidate M&R project is assigned a project prioritization index that is based on the key factors considered. The algorithm used to optimize project selection based on this prioritization index is also presented.

Section 6 analyzes the results of the validation stage and explains agreements and disagreements between the developed plans and actual district PMPs.

Section 7 summarizes the research effort and presents the conclusions.

Section 8 provides recommendations and ideas for future work.

2. LITERATURE REVIEW

2.1 Factors Influencing Prioritization of Pavement M&R Projects

The inclusion of multiple criteria in making infrastructure decisions is increasingly becoming a requisite due to the increased number of stakeholders and higher user expectations from such projects (Sinha et al. 2009). In the area of pavement M&R planning, the decision process must consider all relevant factors, both quantitative and qualitative, simultaneously to determine the best M&R solutions (Cafiso et al. 2002; Frangopol and Liu 2007). Literature is replete with studies that consider multiple criteria in prioritizing pavement M&R projects. The factors used include various condition indices, indicators of benefit, cost parameters, and others that accounts for managerial considerations.

Specific distresses are sometimes used as criteria in prioritizing projects. Flintsch et al. (1998), for instance, used the extent of cracking and rutting as influencing factors while Dessouky et al. (2011) found that the number of failures per mile was used by TxDOT districts in prioritizing M&R projects (Dessouky et al. 2011; Flintsch et al. 1998). The most common way though, is the use of indices that describe pavement condition in terms of a variety of distresses. The most common index used is the Pavement Condition Index (PCI) (Haas et al. 2001). The PCI incorporates data from 19 different types of pavement distresses as well as their severity and quantity (Moazami et al. 2011). In Texas, the Condition Score (CS) replaces PCI as the indicator of pavement condition. In two separate surveys of TxDOT districts, it was found that CS is indeed a primary criterion used in prioritizing M&R projects (Dessouky et al. 2011; Gurganus 2011).

Ride quality is another criterion often considered as it is highly important to road users (Flintsch et al. 1998; Haas et al. 2001). Ride quality is quantified by the Present Serviceability Index (PSI) and the Riding Comfort Index (RCI) in the U.S. and Canada respectively. In Texas, ride quality is represented by the Ride Score (RS) which, again, was found to be a factor in prioritizing M&R projects (Dessouky et al. 2011; Gurganus 2011).

In addition, measures of structural adequacy were also used by several studies as decision criteria. Flintsch et al. (1998) used the structural number while Dessouky et al. (2011) used the structural index to quantify structural adequacy (Dessouky et al. 2011; Flintsch et al. 1998). Deflection testing using the Falling Weight Deflectometer is the widely used method of evaluating structural capacity in pavements (Haas et al. 2001).

Skid resistance, a measure of pavement safety, is another factor of high importance although in terms of road user and manager satisfaction, as long as surface friction is above some defined minimum threshold, it is not an issue (Haas et al. 2001).

Some authors suggest the use of composite indices that aggregate indicators of distresses, ride quality, structural adequacy, and skid resistance in a single measure of pavement overall performance (Haas et al. 2001). For instance, the China Highway Performance Assessment Standards uses the Pavement Quality Index (PQI) which is a weighted average of PCI, Ride Quality Index (RQI), Rutting Depth Index (RDI), and Skid Resistance Index (SRI) (Zhang and Yang 2011). While aggregation of several indices is accompanied by loss of information, such composite indices can nevertheless serve as effective communication tools to summarize pavement performance for administrators, elected officials, and the public (Haas et al. 2001).

Other factors that implicitly reflect pavement condition are pavement age (Dessouky et al. 2011; Šelih et al. 2008) and the number of routine maintenance received by the pavement section in the past (Gurganus 2011). To a lesser extent, effective surface and internal pavement drainage and pavement noise are also used as decision criteria (Haas et al. 2001).

Aside from pavement condition, road managers also tend to prioritize M&R projects that yield greater benefits. For instance traffic volume is often used as a representation of a project's benefit (Dessouky et al. 2011; Flintsch et al. 1998). The greater the volume through a section, the higher the priority will be as timely M&R interventions considerably reduce the operational costs of a great number of vehicles (Moazami et al. 2011). Gurganus (2011) considered AADT and truck AADT as separate criteria in prioritizing M&R projects (Gurganus 2011). Similarly, the road's functional class (e.g., expressway, arterial, access roads) was also found to be of high significance when determining maintenance priorities (Dessouky et al. 2011; Flintsch et al. 1998; Moazami et al. 2011; Shahin et al. 1985).

On the other hand, some authors expressed benefit more precisely as the Area Under the Performance Curve (AUPC) multiplied by section length and traffic volume (Haas et al. 2001; Li et al. 2006; Shahin et al. 1985). This area represents the effectiveness brought about by an M&R activity and can be used as an indicator of benefit. However, it is possible to have the same AUPC even for alternatives that do not maintain the equivalent pavement condition. Thus, Shahin et al. (1985) proposed a utility-weighted performance curve for use in computing the AUPC. In particular, this modification reflects the necessity of repair at a given level of pavement condition. For example, improving a pavement in "fair" condition has greater utility than improving another in "very good" condition (Shahin et al. 1985).

Cost parameters such as the project's initial cost (Šelih et al. 2008), life-cycle cost (Haas et al. 2001; Shahin et al. 1985), and average maintenance cost (Dessouky et al. 2011; Flintsch et al. 1998) also often influence priority decisions. While some consider user-cost (Haas et al. 2001; Šelih et al. 2008) during M&R work as a decision criteria, it is generally not included since user cost is hard to evaluate precisely and objectively and because it is generally much greater than agency costs thereby unduly dominating the decision process (Wu and Flintsch 2009).

Other decision factors have specific application for the agencies that considered them. For example, the geographic region of the project (i.e., desert or mountain) was considered as a prioritization criteria in Arizona where M&R projects in the mountains are assigned higher priorities over those in the desert (Flintsch et al. 1998). In prioritizing repairs of overpasses where traffic lanes underneath must be closed during repair works, Selih et al. (2008) prioritized overpasses that are near to each other over those that are isolated so that multiple overpasses can be simultaneously repaired for a single lane closure (Šelih et al. 2008). In a survey among TxDOT districts, Dessouky et al. (2011) found accident reports, public concerns, and number of heavy loadings to be relevant criteria although with limited influence (Dessouky et al. 2011).

2.2 Multi-Criteria Prioritization of Infrastructure Projects

The inclusion of multiple criteria in M&R decisions produces maintenance plans that are more balanced, cost-effective, rational and justifiable (Sinha et al. 2009). However, the multiple criteria commonly considered in making M&R decisions include both quantifiable and unquantifiable and tangible and intangible factors such that involving them in the decision making process makes the task formidable. Thus, most existing maintenance management systems continue to prioritize M&R projects based purely on a single criterion (e.g., minimize life-cycle cost) (Frangopol and Liu 2007) while in some cases, decision making is performed subjectively altogether (Šelih et al. 2008). Thus, techniques that can systematically perform this task can be of great help for decision makers.

For instance, Flintsch et al. (1998) developed a prioritization formula for pavement M&R projects for use by the Arizona Department of Transportation (ADOT) whereby six pavement attributes are used as the dependent variables to compute a project’s priority number. A survey was distributed to experts who were asked to assign priority numbers to M&R projects with different values for each of the six attributes considered. Linear regression was then used to develop the equation (Flintsch et al. 1998).

Multi-objective optimization techniques such as Genetic Algorithms (GA) (Frangopol and Liu 2007; Fwa et al. 2000) and the weighted sum method (Wu and Flintsch 2009) were also used to optimize M&R decisions by simultaneously considering the objectives of maximizing network performance and minimizing total preservation cost.(Frangopol and Liu 2007; Wu and Flintsch 2009)

A key prerequisite to multiple criteria decision making is to establish the relative importance of the various decision factors considered. When only a single criterion influences the decision, prioritization is done by simply ranking or sorting the alternatives with respect to the selection criterion (Sinha et al. 2009). However, in a multi-criteria framework, weights must first be assigned to each criterion that should reflect the decision maker's perspectives on the relative importance of the criteria among each other. When more than one decision maker is involved, all stakeholders must ideally participate in the weighing process (Cafiso et al. 2002). Sinha et al. (2009) reviewed a number of weighing methods used in the literature. These include the: (1) direct weighing method; (2) observed-derived weights method; (3) gamble method; (4) swing weighing method; (5) indifference trade-off weighing method; and (6) pairwise comparison methods (Sinha et al. 2009).

The pairwise comparison method of weighing multiple criteria is an important feature of the Analytic Hierarchy Process (AHP) which is regarded today as one of the most widely used theory for decision making (Palcic and Lalic 2009). In the AHP, the decision maker carries out simple pairwise comparison judgments among several criteria considered to be influential in attaining a decision goal. The weights of the criteria are computed and used to develop overall priorities for ranking a number of alternatives. The AHP allows for the inclusion and measurement of all important tangible and intangible, quantitatively measurable, and qualitative factors. Unlike the conventional practice of considering only hard economic data while managerial judgment is used in a qualifying manner at the end, AHP explicitly accounts for intangible factors therefore capturing even the subjective preferences of the decision maker (Saaty 1980; Saaty 1982). The AHP involves the following steps: (1) modeling of the problem through a hierarchy of decision factors; (2) pairwise comparisons of the multiple criteria and consistency check; and (3) synthesis of weights to assign priorities for each competing alternatives.

The task of selecting which factors to consider is regarded as the most creative part in making a decision (Saaty and Vargas 2001). In the AHP, the factors are arranged in a hierarchical structure where the top level consists of the overall goal of the decision problem. Below which, are several factors that mainly influence or contribute toward achieving the goal. Below each factor could be another sub-level of factors that influence the factor above and so on. The factors in each level must be of the same order of importance and are assumed to be independent of each other (Saaty 1980). The hierarchy must be constructed so as to represent the problem as thorough as possible but not too complex that it becomes cumbersome to manage. Experience has shown that even simplified idealization of a problem can yield significant findings (Saaty 1980).

To derive the relative weights of the multiple criteria, the AHP requires the decision maker to perform pairwise comparisons of each factor in each level of the hierarchy. The question to the decision maker may be somewhat similar to: Given a pair of factors, which one do you believe is more dominant in contributing to the factor above and how strong is the dominance: equal, weak, strong, absolute (Saaty 1980)? The AHP also has a way to evaluate the consistencies of the decision maker's responses. To limit the number of pairwise comparisons and to ensure greater consistencies, Saaty (1980) recommends that the number of factors in each level be limited to nine under the assumption that the mind can only compare nine factors or less with reasonable consistency (Saaty 1980).

The AHP can also cater to more than one decision maker. One way is through the Delphi process where a group of decision makers debates to reach a consensus as to how to model the problem and what weights must be assigned to each criterion (Saaty 1980). When debate is undesirable, each decision maker may perform the pairwise comparisons individually and the responses are combined using the geometric means of the judgments to represent that of the group (Saaty 1980). When the decision makers are of unequal power or expertise, individual responses may be weighed according to the importance or expertise of the evaluator (Saaty 1982). However, this practice was found to have limited impact on the final rankings of alternatives (Yedla and Shrestha 2007).

The responses for each set of pairwise comparison are expressed in a reciprocal matrix from where the principal eigenvector is computed which when normalized, becomes the vector of priorities. In the absence of a large scale computer to solve the problem exactly, Saaty (1980) provides some alternate procedures that estimate the exact priorities (Saaty 1980).

The usefulness of the AHP is evidenced by the many studies that used it to solve infrastructure project prioritization problems. The AHP was adopted for implementation in the Highway Design and Management software (HDM-4) (Cafiso et al. 2002) and was also proposed for the TxDOT PMIS (Gurganus 2011) and for the municipality of Tehran, Iran (Moazami et al. 2011). Zhang and Yang (2011), on the other hand, used AHP to revise the weights of the four pavement performance criteria used in the China Highway Performance Assessment Standards (Zhang and Yang 2011).

The AHP can also be incorporated with group decision making techniques as carried out by Khademi and Sheikholeslami (2009) where a combined Conference-Delphi-AHP model was implemented to solicit expert opinion for prioritizing low-class roads in Gilan, Iran (Khademi and Sheikholeslami 2009). In the case of prioritizing transportation projects in Taiwan, Su et al. (2006) further considered the variability in the weights assigned to each decision criterion due to different judgment of multiple decision makers. Since the variability in the weights of the criteria can be represented by a probability distribution, several simulations were done where weights vary in each run and consequently, the priority rating of each competing project. Hence, if the priority ratings of a project in different runs spread over a wide range, then it suggests lack of agreement among the decision makers with regard to the desirability of the project and is therefore controversial, deserving low priority (Su et al. 2006).

One obvious drawback of the AHP is that since pairwise comparisons have to be performed to determine: (1) the relative importance of each decision factor; and (2) the relative desirability of each competing alternative, the number of pairwise comparisons increases exponentially as the number of factors and alternatives increase making the process cumbersome and prone to evaluator fatigue and inconsistencies (Su et al. 2006). This limitation was addressed by Šelih et al. (2008) where only the factors were compared while the alternatives were assigned individual ratings. In prioritizing 27 overpass M&R projects, instead of performing pairwise comparison among the competing projects, Šelih et al. (2008) assigned a utility value for each project with respect to each decision criterion. The utility values are linear normalizations of the actual values under each criterion. The overall utility of a project is therefore a synthesis of its utilities and the criteria's corresponding weights. Integer programming was then performed to generate the set of projects to be funded that maximizes overall utility under a given budget (Šelih et al. 2008). Moazami et al. (2011) likewise used this rating approach in prioritizing pavement M&R projects when alternatives are numerous (Moazami et al. 2011).

2.3 Road Segmentation

When prioritizing competing transportation projects, the alternatives may, for example, be: construction of a bridge, railway extension, transit improvements, and so on. In the case of pavement M&R planning, the projects competing for funding are defined by highway segments that are, ideally, requiring the same M&R treatment. Most PMS store data for pavement sections defined by a fixed length. However, the lengths of these data collection sections are usually too short to represent a project for practical purposes. Hence, a critical step in any PMS is the formation of realistic project boundaries. Aside from forming segments that may eventually represent candidate M&R projects for letting, segmentation is also desirable in that it may virtually reduce the size of the data for analysis.

The identification of homogeneous pavement segments remains, in general, a subjective process relying heavily on the judgment and experience of the engineer. A lack of analysis on this area results to a “conservative” ad hoc approach that tends to cater for the sections in poorer conditions thus overproviding for much of the other pavement sections leading to uneconomical decisions. Hence, the cost-effectiveness and optimality of an M&R plan is heavily influenced by the accurate identification of homogeneous segments (Jordaan 2002; Thomas 2003).

Benneth (2004) discussed three basic approaches to segmentation: fixed length segments, dynamic segments, and static segments. Fixed length segments do not change over time and are created to match fixed features like mile posts or city blocks. This approach therefore ignores pavement attributes in creating segments (Bennett 2004). Latimer et al. (2004) found that this type of segmentation poorly predicts maintenance requirements than those which consider pavement attributes (Latimer et al. 2004).

Dynamic segments on the other hand, divide the network based on the homogeneity of their attributes (e.g., roughness). Since these attributes change every year, segmentation is likewise done every year. Static segments lie between these two extreme approaches where segments are still created based on their attributes but the boundaries are maintained for a number of years. Of these three approaches, Benneth (2004) states that static segmentation is the most useful as it allows trends in condition over time to be monitored, a task that is difficult to achieve in dynamic segmentation. Benneth (2004) suggests that the formed static segments can be reviewed every 3-5 years to obtain most of the benefits of dynamic segmentation while maintaining stability in the PMS (Bennett 2004).

Ensuring the homogeneity of the formed segments is a critical prerequisite when adopting either a dynamic or static segmentation scheme since once a segment is created, it is assumed that the attributes characterizing the segment are representative of its condition (Latimer et al. 2004). One relatively straightforward method for delineating statistically homogeneous segments is the cumulative difference algorithm (American Association of State Highway and Transportation Officials 1993). The difference between values of a certain pavement attribute and an established threshold (e.g., the network average) are computed and added cumulatively. Points where the cumulative difference graph changes slope marks changes in the measured attribute and hence, in the uniformity of the pavement. This method can be applied using any numerical pavement attribute (e.g., condition indices, deflection measurements, roughness, etc.) or a combination of these.

For instance, Jordaan (2002) developed a methodology that allows the combination of several attributes into one cumulative difference graph. Deflection bowl measurements at different distances were normalized and then combined so that segment boundaries are established based not only on the homogeneity in one attribute but on several (Jordaan 2002).

As more attributes are considered in applying the cumulative difference method, the formed segments become shorter (Bennett 2004). And to be considered candidate M&R projects for letting purposes, the segments must be as long as possible to avoid frequent mobilizations of paving equipment (Duanyi et al. 2010). Hence, a minimum length criterion is also applied to prevent unreasonably short segments from being formed. This can be done by comparing adjacent sections and if the attributes are close to each other, they can be combined to create a single segment. Moreover, in deciding which attributes to consider in segmentation, the attributes that influence maintenance treatment selection should be given preference (Bennett 2004).

Aside from the cumulative difference method, there are also a number of algorithms developed to address the segmentation problem. For instance, Duanyi et al. (2010) uses cluster analysis theory to segment the road network. Using the length of transverse cracks, length of longitudinal cracks, rut depth, and friction coefficient as the indices, the road network was divided into three classes of segments characterized by the quantities of the distresses above. Each class therefore requires a unique M&R treatment based on the quantities of these indices (Duanyi et al. 2010).

Since boundaries of road segments must be established where there are significant changes in road condition (i.e., change-points). Thomas (2003) developed a methodology where the posterior probability for a change somewhere along the length of the road is computed. Boundaries are then set wherever the posterior probability computed is high. For example, a posterior probability of a change in condition of 0.5

means that the evidence that a change-point exists is just as strong as the evidence for the absence of a change-point (Thomas 2003).

Yang et al. (2008) on the other hand, uses spatial clustering algorithm using fuzzy c-mean concept to determine change-points by minimizing the pavement condition variation in each formed segment while considering initial set-up cost, minimal project length and cost, and barriers, such as bridges, and district boundaries (Yang et al. 2008). The decision as to which segmentation method to adopt is therefore a compromise between reliability of the predicted results and the complexity of the analysis.

Regardless of the algorithm, segmentation always has limitations. Pavement attributes have inherent variations in their measurements that preclude true homogeneity among the segments formed (Bennett 2004). Localized areas of relatively good or relatively poor pavements may exist due to localized factors within the segment formed. These localized areas may be obscured in longer segments resulting in less accurate predictions of the segments' M&R needs (Latimer et al. 2004). These cases must be analyzed separately, taking into account the practical implications of changing the M&R treatment over very short lengths (Jordaan 2002).

Benneth (2004) suggests that agencies should verify in the field the soundness of the segments formed as a part of their quality assurance process. For example, segments that are incorrectly formed due to data errors can be identified and corrected in this process. Another approach is for engineers to run the segmentation algorithm and then assign treatments to the segments. When similar treatments are applied to adjacent segments, they can be combined to form a larger one. These cases may occur when variations in the raw data, which may appear to be significant, cause limited impact on M&R treatment selections (Bennett 2004).

2.4 Optimization of M&R Project Selection

Many states allocate their limited budgets by using sufficiency ratings or empirical formulas to priority rank deficient infrastructure assets. Usually, a priority rank formula translates physical conditions and level-of-service deficiencies into a priority index for every asset. The assets are then ranked according to their priority indexes for receiving improvement funding. Priority ranking formulas cannot select the optimal improvement alternative for an asset nor can they optimize net benefits expected from the budget granted. Thus, a systematic algorithm is needed for efficient allocation of limited M&R budget (Farid et al. 1994).

Project selection problems which seek the optimum set of projects that maximizes a certain attribute (e.g., benefit) under some resource constraint/s (e.g. budget) can be modeled as zero-one programming problems (also called knapsack problems). These are a type of combinatorial optimization problem that can be solved using Integer Programming (IP). However, as the size of the problem increases, the computational time required to achieve the optimum solution increases exponentially, limiting its applicability to moderately sized problems. For majority of large real-world problems, it is more realistic to design a solution procedure which will generate, within a reasonable time, near-optimum solutions (Foulds 1984).

Toyoda presented a new method for obtaining such near-optimum solutions to knapsack problems using as an example a problem involving the selection of an optimal package of projects under limited resources. This algorithm was proven to produce very good approximate solutions to large-scale knapsack problems within a relatively short computational time (Toyoda 1975). This was implemented in the Rehabilitation and Maintenance Optimization System (RAMS) that was developed for use by TxDOT district offices (Ahmed et al. 1978).

Another algorithm, and perhaps the most widely used especially in infrastructure project selection, is the Incremental Benefit-Cost (IBC) analysis which is implemented in the U.S. Army Corps of Engineers PAVER PMS. IBC can be applied in either project- or network-level pavement management where its goal is to maximize benefit from limited M&R funds (Shahin et al. 1985). It does this by evaluating the marginal benefit accrued from advancing from a lighter M&R alternative to a heavier one and the corresponding marginal increase in cost (Farid et al. 1994). As a consequence, as more funds become available, more high-benefit M&R projects are selected for implementation.

3. PROJECT FORMATION SCHEMES BASED ON AVAILABLE PAVEMENT MANAGEMENT DATA

TxDOT's PMIS stores roadway data for every data collection section (which is typically 0.5 miles long). In contrast, agencies prioritize and let M&R projects that extend over longer roadway segments typically ranging from 2 to 10 miles. Hence, contiguous data collection sections must be grouped together to form realistic M&R projects. This section of the thesis first introduces information found in the TxDOT PMIS database, especially data collection section attributes that are pertinent to project formation and prioritization. Then, two M&R project formation schemes are presented. The first scheme is the widely used Cumulative Difference Algorithm (CDA) which groups sections based on homogeneity. The second scheme was developed in this study and is called the Proximity to Deficient Areas (PDA) approach, where M&R projects are formed around defective pavement sections. These schemes will be incorporated in the M&R project prioritization methodology.

3.1 PMIS Data Elements Pertinent to the Project Prioritization Methodology

The TxDOT PMIS locates a data collection section through its unique highway ID and Reference Markers (RM). The highway ID contains information on the: (1) route type; (2) highway number; and (3) roadbed on which the data collection section stands. Figure 3.1 shows an example of a highway ID (Texas Department of Transportation 2010).

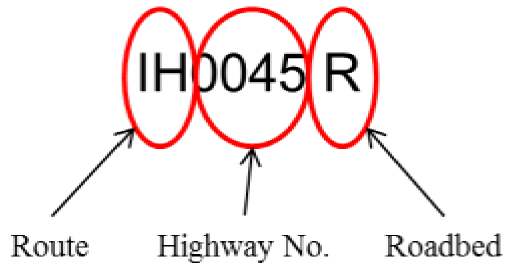


Figure 3.1 PMIS Highway ID

Table 3.1 lists the types of routes used by TxDOT (from major to minor) and the corresponding prefixes. Figure 3.2 illustrates the different types of roadbeds (Texas Department of Transportation 2010).

Table 3.1 PMIS Route Types

Route Description	Prefix
Interstate Highway	IH
US Highway	US
State Highway (includes NASA, OSR)	SH
Business Interstate	BI
Business US Highway	BU
Business State Highway	BS
Farm to Market	FM
Business Farm to Market	BF
Park Road	PR

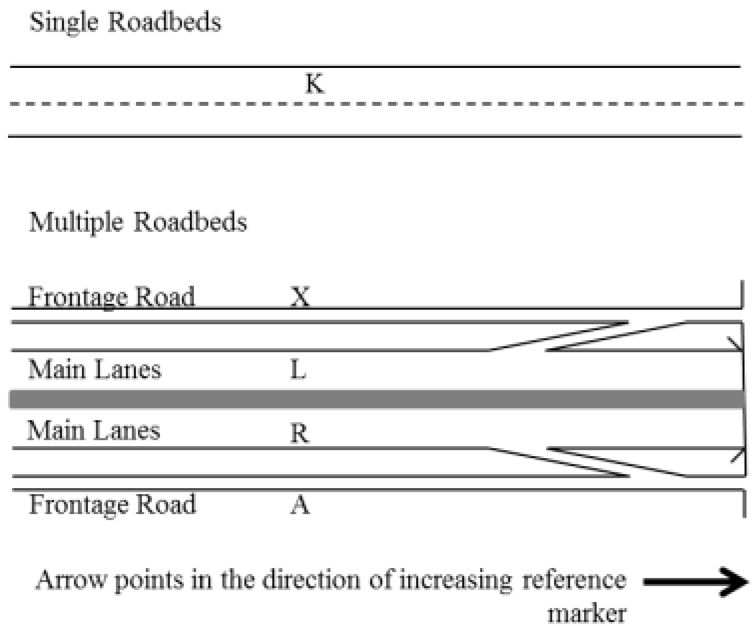


Figure 3.2 PMIS Roadbed Types

Following the highway ID are four reference markers that specify the exact location of the data collection section along the highway. As an example, Figure 3.3 indicates a data collection section that starts exactly at RM 173 [i.e., “00” miles past the beginning reference marker (BRM)] and ends 0.5 miles past RM 173 [i.e., 0.5 mile past the ending reference marker (ERM)], for a total section length of 0.5 miles.

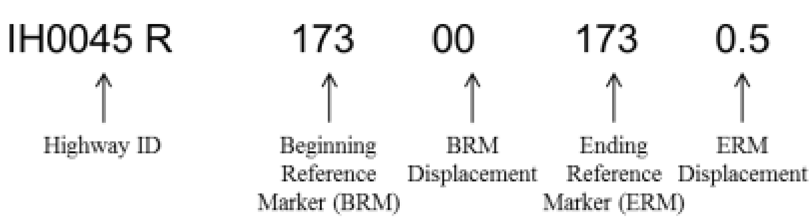


Figure 3.3 PMIS Reference Markers

The highway ID and reference markers are followed by a number of attributes that characterize the data collection section and are pertinent to the proposed M&R project prioritization methodology (see Table 3.2). These attributes are described in further details in PMIS manuals (Texas Department of Transportation 2011).

Table 3.2 Data Attributes used in the Developed M&R Project Prioritization Methodology

Category	Data Attributes
Pavement Condition	Distress Score (DS), Condition Score (CS), and Ride Score (RS)
Roadway Geometry	Number of Lanes and Section Length
Traffic	AADT, Truck AADT (Percentage), and Speed Limit
Pavement Type and Projected Life	Pavement Type Broad Code [C (Continuously Reinforced), J (Jointed Concrete), A (Asphaltic Concrete)], Pavement Family [CRCP, JCP, A (Thick ACP, Intermediate ACP, Overlaid ACP), B (Composite Pavement, Concrete Pavement Overlaid with ACP), C (Thin ACP, Thin-Surfaced ACP)] and Projected 20-year Equivalent Single Axle Load
Location	District Name and Zone Number

Specifically, DS is a pavement surface condition index used to rate a pavement according to the type and amount of key distresses present. DS has a 1-100 scale (with 100 representing no or minimal distress). RS, on the other hand, is a measure of ride quality with a 0.1 (worst ride) to 5.0 (best ride) scale. CS combines DS and RS and has a 1-100 scale (with 100 representing no or minimal distress and roughness).

3.1.1 Adjustment of Questionable Data

The raw PMIS database can contain questionable or erroneous entries. For this study, key pavement condition indicators (namely CS, DS, and RS) were checked and corrected.

The CS value for each pavement section is checked against a minimum value (a CS of 20, in this case). Such low CS values are considered questionable because TxDOT is unlikely to allow a roadway section to deteriorate to such very poor condition. If the CS is less than 20, for example, the CS, DS, and RS are adjusted as follows:

- CS greater than zero and less than 20: Replace CS, DS, and RS with that of the average values of the adjacent sections.
- CS is equal to zero: A CS may be set to zero due to ongoing M&R work during the data collection process or lack of condition data. In this case, the CS, DS, and RS are adjusted as follows:
    - If an M&R treatment was applied in the data collection year or the past 1–2 years (based on pavement work history), reset CS to 100, DS to 100, and RS to 4.8.
    - If no M&R treatment was applied in the past 1-2 years, replace CS, DS, and RS with that of the average values of the adjacent sections.

This procedure is illustrated in a hypothetical example shown in Table 3.3.

Table 3.3 Example of Adjusting Erroneous Condition Data

Pavement Section No.	1	2	3	4	5	6	7	8
BRM-Displacement	426-0.0	426-0.5	426-1.0	426-1.5	428-0.0	428-0.5	428-1.0	428-1.5
ERM-Displacement	426-0.5	426-1.0	426-1.5	428-0.0	428-0.5	428-1.0	428-1.5	430-0.0
2011 CS	90	17	86	0	0	70	0	76
M&R in 2011, 2010, 2009?	N	N	N	Y	Y	N	N	N
2010 CS	92	89	88	56	54	71	75	78
Adj 2011 CS	90[1]	88[2]	86[1]	100[3]	100[3]	70[1]	73[2]	76[1]

[1]No adjustment is needed.
[2]Erroneous entry: Adjusted CS (88) is the average of CS from adjacent sections (90 and 86).
[3]Section was under M&R during data collection: Set CS to 100.

3.1.2 Computing Rate of Deterioration for Condition Score

The CS rate of deterioration (CSRD) is not directly available in the PMIS database; however, it can be computed using CS data from past years.

The CSRD of a pavement section was computed as the average annual drop in CS in the past 1–3 years. Table 3.4 shows sample computations for this parameter.

Table 3.4 Example of Computing CSRD

Case	Drop in CS			CSRD,
	2008–2009	2009–2010	2010–2011	CS points/year
1	8	13	23	14.67
2	NA[1]	22	30	26
3	NA	NA	3	3
4	NA	17	NA	0

[1]NA: Not Applicable due to increase in CS

3.2 Cumulative Difference Algorithm for Forming M&R Projects

The cumulative difference algorithm can be used to group homogeneous data collection sections into segments that can be maintained independently and thus represent potential M&R projects.

In this project formation scheme, data collection sections can only be grouped together if the following conditions are met:

- Sections must belong to the same highway (i.e., same highway ID);
- Sections must be on the same roadbed;
- Sections must be contiguous (as indicated by their RMs); and
- Sections must be of the same pavement family.

In addition, this project formation scheme allows for imposing minimum and maximum lengths on the projects formed.

The example shown in Figure 3.4 illustrates the CDA segmentation process based on homogeneity in CS. The cumulative difference between each section's CS and a CS threshold value of 70 is plotted. In theory, change-points in the cumulative difference plot indicate boundaries between homogeneous segments. In this example, the seven marked lines indicate boundaries between the eight homogeneous segments *a* to *h*. Assuming that each PMIS section in this case is 0.5-miles long and that a minimum project length of 2 miles is imposed, segments *c*, *d*, *e*, and *g* would be too short to form management sections and thus boundaries 3, 4, and 7 are discounted. Consequently, the CS-based homogeneous segments are delineated by boundaries 1, 2, 5, and 6 (see red lines).

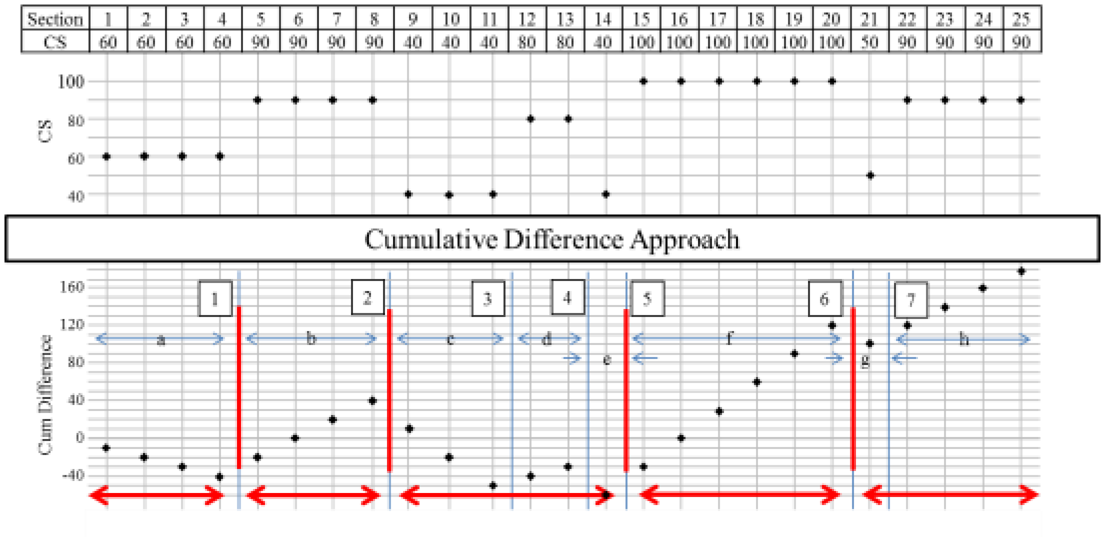


Figure 3.4 Example of the Cumulative Difference Approach

The CDA was also applied using DS and projected cumulative ESALS to produce segments that are homogeneous in both condition and carried truck traffic. The CS and DS segmentation thresholds can be set to delineate stretches of roadways that have acceptable condition (e.g., CS greater than 70 and DS greater than 80) from stretches with unacceptable condition. The ESAL threshold can be set to delineate stretches of roadways that have above-average cumulative design ESALs from stretches that have below-average cumulative design ESALs.

Subdividing a roadway based on uniformity in three attributes (i.e., CS, DS, and cumulative ESALs) naturally results in three different sets of segment boundaries. Furthermore, these three sets may not coincide with each other. Consider the diagram in Figure 3.5 for example. It can be seen that the boundary between segment 1 and 2 coincide for all segmentation criteria. For the other segments, however, the boundaries do not coincide. Theoretically, whenever a boundary is identified from any of the above criteria, a separate segment is formed, as shown in the set labeled "Theoretical Segments." However, this method will inevitably create segments that are too short (e.g., less than 2 miles) such as segments 3, 5, 6, 7, 9, and 10 in Figure 3.5. To meet the minimum length requirement, a "stitching" rule was devised, as follows:

- When the boundary from CS conflicts with that from DS or ESAL, the boundary from CS is used.
- If the conflict is between DS and ESALs, the DS boundary is used.

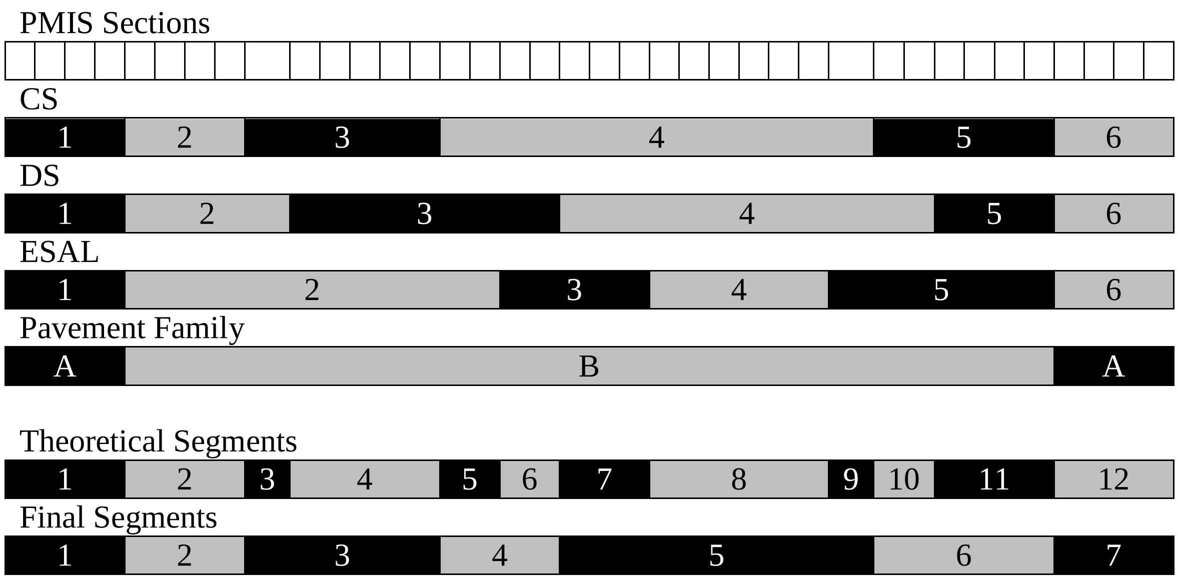


Figure 3.5 Example of Reconciling Multiple Sets of Boundaries

The results of applying this stitching rule are shown and labeled as "Final Segments" in Figure 3.5. In some cases, the segments formed may exceed a required maximum length (e.g., 10 miles). In these cases, the long stretches are divided equally to remain within the maximum length limit. For example, if the maximum length limit is set to 10 miles, a 14-mile segment will be divided into two 7-mile segments. Finally, it should be noted that even after the stitching process is applied, some segments may remain shorter than the minimum length limit (e.g., entire road is too short, an isolated short stretch of a certain pavement family, etc.).

While the CDA approach is widely used by transportation agencies, it can potentially mask localized deficient areas due to the averaging effect. Thus, an alternative project formation scheme was developed in this study to overcome this potential drawback, as discussed next.

3.3 Proximity to Deficient Areas Approach for Forming M&R Projects

The Proximity to Deficient Areas (PDA) approach uses an M&R trigger criteria (e.g., CS < 80) to identify deficient localized areas (i.e., data collection sections that fail to meet a minimum performance threshold). Realistic M&R projects are then formed around these deficient areas by grouping together nearby data collection sections. Similar to the CDA, the conditions listed in section 3. 2 must also be met for data collection sections to be grouped together.

Figure 3.6 displays the same CS data that was used for demonstrating the CDA approach, but the PDA approach is used in this case instead of the CDA approach to delineate project limits. First, sections with attributes falling below the M&R trigger value (i.e., CS of 80) are flagged (see red dots). This results in segments *a*, *b*, *c*, and *d*, being initially formed. As in the CDA, notice that segments *b*, *c*, and *d* are too short to constitute realistic M&R projects while segment *a* meets the minimum project length limit. In these cases, the algorithm joins short deficient segments with other deficient segments that are less than two miles apart (see segments *b* and *c* being joined). When the gap between localized deficient sections is greater than two miles, each localized deficient section is expanded by one mile of roadway on both sides (see enlarged segment *d*). This approach ensures that independent M&R projects are separated by at least the minimum project length limit (two miles in this example); the maximum project length limit is applied similar to that in the CDA. Finally, similar to the CDA approach, some segments may still remain shorter than the minimum length projects limit due to exceptional situations (e.g., entire road is too short, an isolated short stretch of a certain pavement family, etc.).

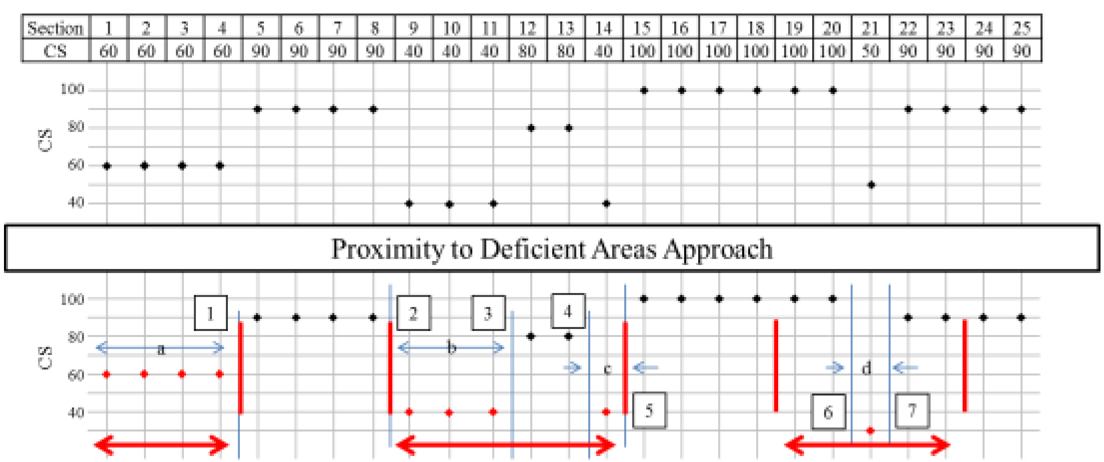


Figure 3.6 Example of the Proximity to Deficient Areas Approach

3.4 Aggregation of Attribute Data

To account for variability within the grouped sections and to reduce the potential for masking local poor areas, the attribute data (e.g., CS, DS, AADT) for the segments are computed as shown in Equation 3.1; where $Attribute_R$ is the segment attribute (e.g., CS, DS, AADT) at reliability level R; $\bar{x}_w$ is the weighted (by length) average of the attribute for the segment; Z_R is the standard normal deviate corresponding to reliability level R; and sd_w is the weighted (by length) standard deviation of attribute values in the segment.

$$Attribute_R = \bar{x}_w - Z_R \mathrm{sd}_w \qquad \text{Equation 3.1}$$

The formula for weighted standard deviation, sd_w, is given by Equation 3.2 where w_i is the weight for the ith observation and N' is the number of non-zero weights (Heckert and Filliben 2003).

$$sd_w = \sqrt{\frac{\sum_{i=1}^{N} w_i (x_i - \bar{x}_w)^2}{\frac{(N' - 1)\sum_{i=1}^{N} w_i}{N'}}} \qquad \text{Equation 3.2}$$

Consider the example shown in Table 3.5. Assuming a CS trigger value of 80, notice that only Section 5 in this segment needs M&R. When the average CS (i.e., 50% reliability) is used to represent the condition of this group of sections, the segment would be deemed not requiring treatment (i.e., 87.4 > 80). This is an example when a localized deficiency is obscured by relatively good neighboring sections. However, if the reliability is increased to 80%, the segment would be triggered for M&R and will be a candidate M&R project.

Table 3.5 Example of Applying Reliability in Computing Segment Condition

Section No.	Section Length (mi)	CS
1	0.5	95
2	0.5	96
3	0.5	86
4	0.5	92
5	0.5	58
6	0.5	90
7	0.5	82
8	0.5	96
9	0.5	89
10	0.5	90
Weighted Ave. CS		87.4
Weighted Std. Dev.		11.2467
Group CS (50% Reliability)		87.4
Group CS (80% Reliability)		77.9

3.5 Processing of User-Defined Skid, Structural, and Visual Assessment Ratings

As discussed earlier, not all pavement condition indicators are available in the PMIS database. Specifically, PMIS does not contain data on vital indicators such as skid assessment, structural assessment, and visual assessment of district engineers. Therefore, an additional step was designed to allow district staff to enter binary “Adequate/ Inadequate” ratings for these condition indicators.

The district staff specifies the beginning and ending of the road segments that have been rated for skid resistance, structural capacity, and that have been assessed visually and then assigns “Adequate” or “Inadequate” ratings for these indicators (called SKID, STRUCT, and VISUAL, respectively).

The Beginning Reference Marker (BRM) and End Reference Marker (ERM) specified by the district staff for SKID, STRUCT, and/or VISUAL may or may not coincide with the segments created by the CDA or PDA algorithms. Thus, a simple rule was used to govern the extrapolation of these ratings to the computed segments: when a portion of a computed segment is rated, the prevailing assessment within that portion is extrapolated to the rest of the group only if that portion represents or exceeds a minimum percentage of the segment. In this research, the default limit is set to 10% of segment length.

Figure 3.7 provides examples of extrapolating district assessment ratings. In Case 1, eight of the 20 PMIS sections in the road segment (i.e., 40%) have been assigned inadequate rating. Since this is more than the default limit of 10% of the segment, this rating is extrapolated to the rest of the group. In Case 2, the prevailing assessment is adequate, hence the group is rated as adequate. In Case 3, less than 10% of the segment has been rated. In this case, the rating is ignored and the segment rating is "Null".

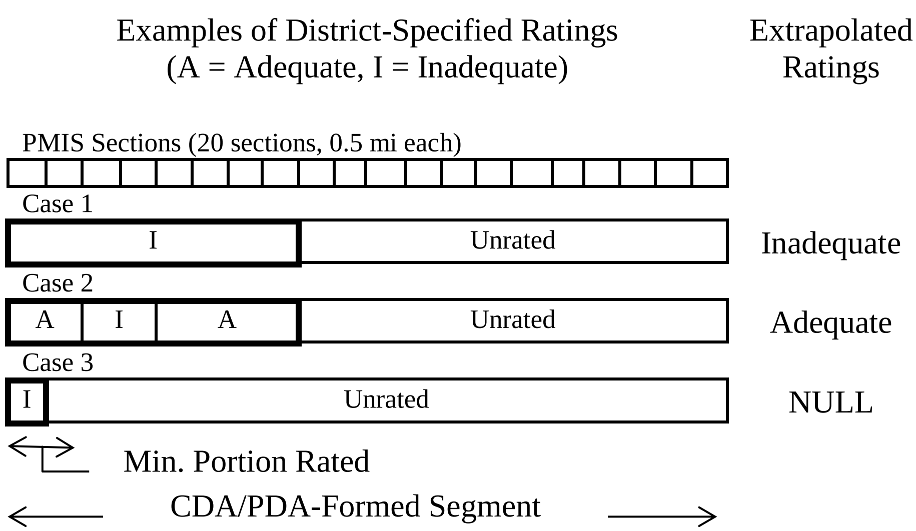


Figure 3.7 Extrapolation of Partial SKID, STRUCT, or VISUAL Assessments to Road Segment Assessments

3.6 Forced Projects

District staff can also enter the boundaries of forced M&R projects. A forced project is defined as a roadway segment that has been assigned an M&R treatment by district engineers and is automatically funded; therefore does not undergo the project prioritization process.

The procedure for determining a common forced treatment for a group is similar to that used for extrapolating SKID, STRUCT, and VISUAL ratings. However, in this case, instead of specifying “Adequate” or “Inadequate,” the M&R type of the project (i.e., PM = Preventive Maintenance, LR = Light Rehabilitation, MR = Medium Rehabilitation, HR = Heavy Rehabilitation) is specified. Figure 3.8 show three examples of forced M&R projects.

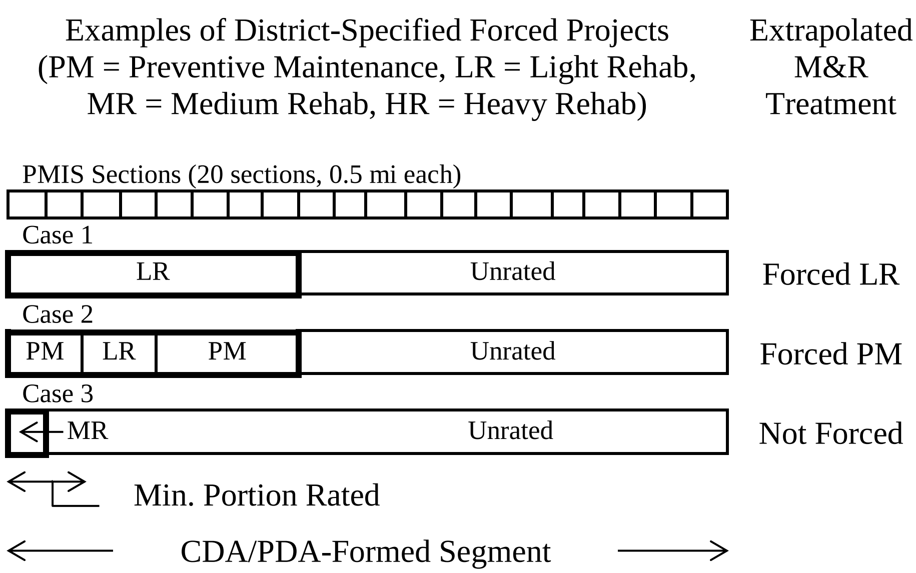


Figure 3.8 Extrapolation of Forced M&R Treatments to Segment Treatments

3.7 Comparison of the CDA and the PDA Approach

Figure 3.9 juxtaposes the segments formed using the CDA and the PDA approach. Notice that the average CS for the formed segments is shown. Important distinctions between the two are discussed next.

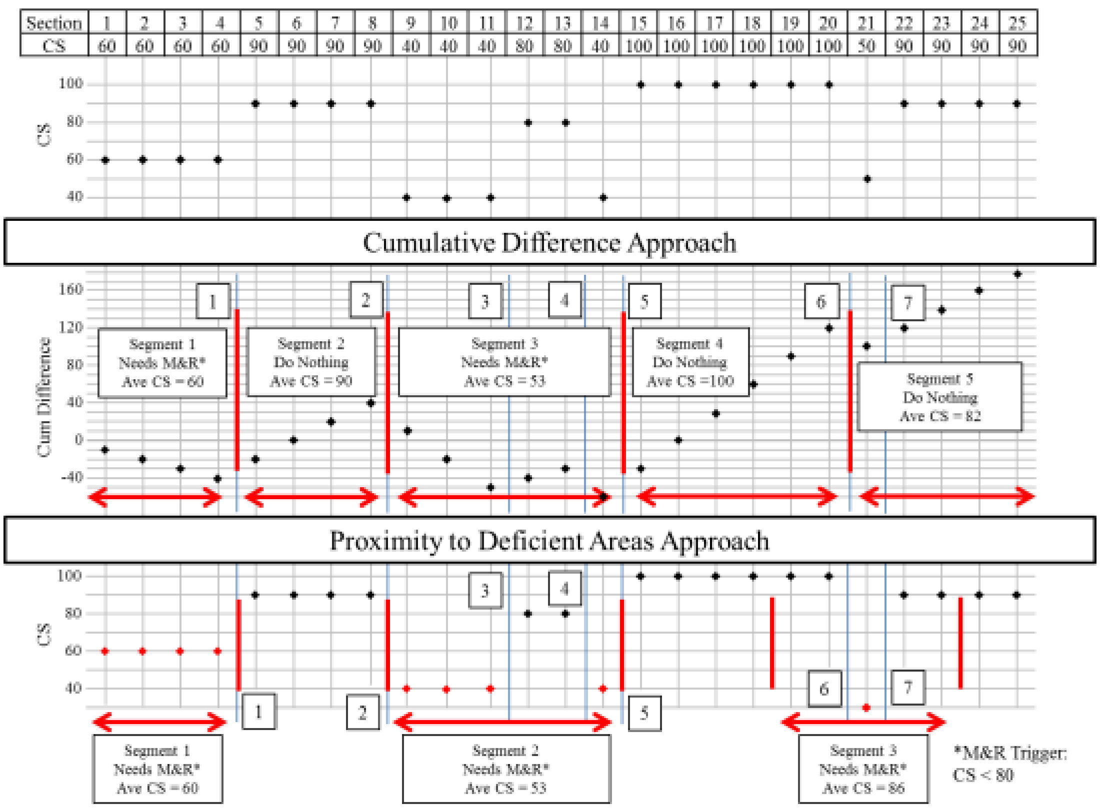


Figure 3.9 Comparison of CDA- and PDA-Formed Boundaries

3.7.1 Trigger of M&R

In the CDA, pavement segments are formed first and then assessed for M&R. A segment is triggered for M&R if its aggregated condition meets the trigger criteria. For example, if the M&R trigger criterion is average CS < 80, CDA-formed segments 1 and 3 would require M&R; whereas segments 2, 4, and 5 would not be triggered for M&R.

In the PDA, each data collection section (not the segment average) is assessed first and then potential projects are formed around sections that are triggered for M&R. For example, PDA-formed segment 3 is formed as a potential M&R project due to deficient local area (data collection section 21). This same segment of the roadway was not triggered for M&R by the CDA because of the effect of aggregation (e.g., averaging). This shows that the CDA may potentially obscure localized deficient areas especially when pavement condition among adjacent sections is highly varied.

3.7.2 Static Segmentation Versus Dynamic Segmentation

In the CDA, the aggregated condition of each segment is projected for the following year and segment boundaries are kept constant over the planning horizon (e.g., four years). This segmentation approach is commonly known as static segmentation where each segment is assumed to behave uniformly as a unit (Bennett 2004). Hence, homogeneity within the segment is critical so that the effect of averaging is minimized and that the projected pavement condition would be close to reality.

In contrast, the PDA predicts pavement condition for the individual data collection sections. In addition, project formation is applied every year (i.e., dynamic segmentation) (Bennett 2004). Thus, uniformity in condition within each segment is not as critical in the PDA approach as it is in the CDA.

3.7.3 Presentation of Network Condition

In the CDA approach, the aggregated condition is used in reporting network condition (e.g., average CS, percent lane-miles classified as "poor", etc.). This was done to be consistent with the premise of the CDA approach where a segment attribute is assumed to be representative of the whole segment. In contrast, the PDA approach retains the data collection section attributes.

Consider Figure 3.9 for example. Assuming that all segments needing M&R are treated and that their CS are reset to 100, the CDA approach would report the backlog (i.e., percent of network lane-miles with CS below 70) as 0% even though, in reality, data collection section 21 has a CS of 50.

4. DECISION FACTORS INFLUENCING M&R PROJECT PRIORITIZATION

A comprehensive approach to pavement M&R project prioritization involves consideration of multiple criteria. In this research, a variety of short-term and long-term criteria that are deemed influential in prioritizing M&R projects were considered. This section introduces and describes the decision criteria used and presents the process of determining their importance weights using a Multi-Criteria Decision Making (MCDM) technique known as the Analytic Hierarchy Process (AHP). The calculated weights are also shown and analyzed.

4.1 Short-Term and Long-Term Factors

Short-term criteria include factors that represent the roadway current status and thus tend to prioritize M&R projects that reap immediate improvements. On the other hand, long-term criteria include factors that represent the future benefits and costs accrued from maintenance and rehabilitation projects. The five main criteria are: pavement Current Condition (CC), Current Traffic Volume (CTV), Initial Cost (IC), Long-Term Performance Benefit (LTPB), and Life-Cycle Cost (LCC). The first three criteria were assumed to reflect short-term prioritization while the last two were assumed to reflect a long-term approach. The following describes each criterion in detail.

- **Pavement Current Condition (CC)**. This is a composite index that reflects the overall health of the pavement as described by the following sub-criteria:
    - **Distress Score (DS)**. A pavement surface condition index used by TxDOT to rate a pavement according to the type and amount of key distresses present. DS has a 1–100 scale (with 100 representing no or minimal distress). DS was considered as a sub-criterion of current condition for maintenance projects only. DS data are available in the PMIS.
    - **Ride Score (RS)**. A 0.1 (worst ride) to 5.0 (best ride) measure of ride quality. RS data are also found in the PMIS.
    - **Condition Score (CS)**. A standard index used by TxDOT that combines distress score and ride score. CS has a 1–100 scale (with 100 representing no or minimal distress and roughness). Since rehabilitation activities tend to improve both surface condition and ride quality, CS was considered a sub-criterion of current condition only for rehabilitation projects. CS data are available in the PMIS.
    - **CS Rate of Deterioration (CSRD)**. A factor that is measured in terms of the drop in CS per year. CSRD is computed as the average drop in CS for the last three years.
    - **Skid Assessment (SKID)**. An "Adequate/Inadequate" rating of the skid resistance of the pavement surface and thus is related to safety. Note that the PMIS database has data fields for Skid Score (1=low

skid resistance, 100=high skid resistance) but in many cases, the values are not available.

    - **Structural Assessment (STRUCT)**. A measure of the structural soundness of the pavement. It is an “Adequate/Inadequate” rating based on structural capacity tests (e.g., Falling-Weight Deflectometer). Note also that the PMIS has data fields for Structural Strength Index (1= very weak, 100=very strong) but in many cases, the values are not available.
    - **Visual Assessment (VISUAL)**. An “Adequate/Inadequate” rating based on overall visual assessment of pavement condition conducted by district staff.

- **Current Traffic Volume (CTV)**. Usage is a common measure of benefit. That is, the higher the number of users that will be impacted by the improvement, the higher would be its priority. In this research, current traffic volume is described by two sub-criteria:
    - **Annual Average Daily Traffic (AADT)**. This parameter represents overall usage of the road and is available in the PMIS.
    - **Truck AADT (TAADT)**. This parameter specifically represents usage by commercial vehicles and therefore is a proxy for the economic importance of the road. Truck traffic as a percentage of AADT can be found in the PMIS.

- **Initial Cost (IC)**. This factor was considered since a short-term outlook will usually favor M&R projects with lower initial cost.
- **Long-Term Performance Benefit (LTPB)**. This factor is measured by the Area Under the Performance Curve (AUPC) as shown in Figure 4.1. It represents the long-term effectiveness of an M&R treatment and has been used in past studies as a measure of long-term benefit (Abaza and Murad 2010; Butt et al. 1994; Cheng et al. 2010). This parameter quantifies long-term benefit by considering both the condition improvement caused by the treatment and the life of the treatment. The greater the AUPC, the greater the benefit in the long-term, and therefore, the higher the priority. This is in contrast to a short-term view where projects with immediate benefits are favored.

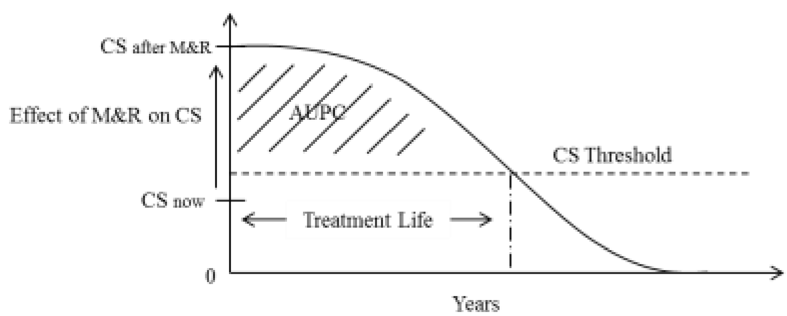


Figure 4.1 Graphical Illustration of Area Under the Performance Curve

- **Life-Cycle Cost (LCC)**. A widely used metric that represents the long-term costs of present actions. In a long-term approach, the lower the LCC, the higher the priority. This is in contrast to a short-term view where only initial cost is considered and subsequent costs are ignored.

The relative importance of these factors were determined using the AHP. The AHP involves the following steps: (1) modeling of the problem through a hierarchy of decision factors; (2) pairwise comparisons of the multiple criteria and consistency check; and (3) synthesis of weights (Saaty and Vargas 2001). The first two steps are discussed next while the synthesis of weights is discussed in section 5.5.1 as it applies to the computation of the project priority index.

4.2 Hierarchy of Decision Factors

The goal of this step is to construct a hierarchy of criteria that closely models the decision problem in reality. The multiple decision criteria are arranged in a hierarchy whereby the objective of the decision problem is set at the top. Beneath this are the relevant criteria that mainly influence the objective. Additional sub-criteria may then be added below each main criterion if necessary. Since the objective of this research was to determine the priority of candidate M&R projects, the top of the hierarchy was called the priority score. It is a project priority index that quantifies the importance of each M&R project as influenced by the main criteria and sub-criteria discussed previously. This hierarchy is illustrated in Figure 4.2.

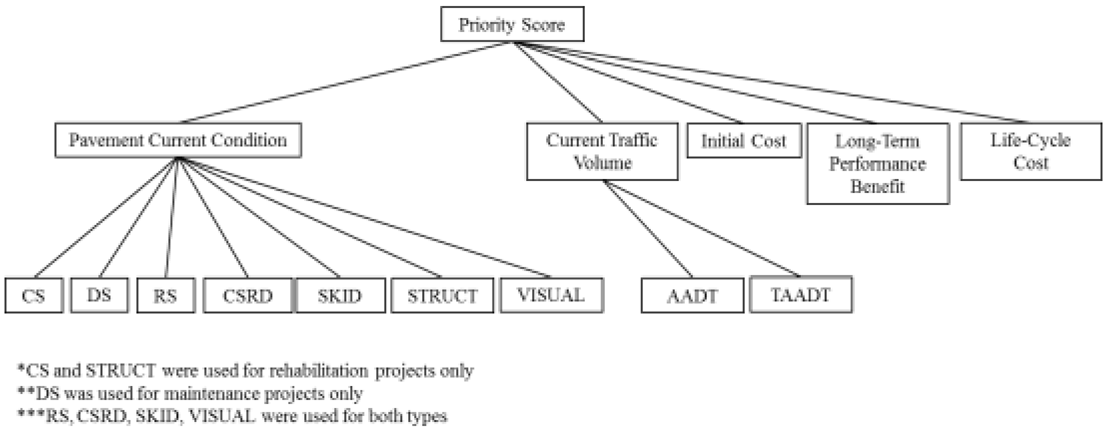


Figure 4.2 Hierarchy of Decision Factors

In constructing the hierarchy in Figure 4.2, the following guidelines were observed (Saaty 1980; Saaty 1982; Saaty and Vargas 2001):

- The hierarchy must be comprehensive but not too complex to be cumbersome.
- The factors in each cluster (i.e., group of sub-factors extending from the same factor) must be of the same order of importance.
- The factors in each cluster must be independent or at least be sufficiently different from each other.
- The factors in each cluster must be limited to nine to ensure consistency.

To meet these guidelines, it was necessary to construct a two-level hierarchy for this problem. Since a number of indexes are used to describe pavement condition, these must be aggregated first to be compared to the other criteria in terms of importance. The same applies for the two indicators of traffic volume. Had the individual indexes been placed alongside the main criteria, too much weight might have been assigned to them. This would result in the indexes (e.g., CS) disproportionately dominating the decision problem and overshadowing the other factors (e.g., Life-Cycle Cost). This scenario would have been characteristic of a worst-first approach where pavements with poor condition are given higher priority.

The rationale for requiring independence among the decision factors is to avoid double counting of certain attributes. To meet this requirement, CS and DS were only considered as sub-criteria one at a time (i.e., CS as a sub-criterion of current condition for rehabilitation projects while DS as a sub-criterion of current condition for maintenance projects). The other factors are fairly independent from each other.

The number of factors in each cluster is limited to nine due to the assumption of the limited capacity of the mind to compare more than nine factors simultaneously (Saaty 1980). As can be seen in Figure 4.2, this requirement is met since the largest cluster in this hierarchy consists of six factors (i.e., CS, CSRD, RS, SKID, STRUCT, and VISUAL). This arrangement ensures that performing pairwise comparisons among the decision factors is manageable.

4.3 Pairwise Comparison and Consistency Check

4.3.1 Sets of Comparisons

In this step, the factors within the same cluster are to be compared with one another, one pair at a time, as to their influence on the decision goal or on the parent factor. The number of comparisons in each cluster is determined by Equation 4.1 where *n* is the number of factors to be compared.

$$No.of\ Comparisons = \frac{n(n-1)}{2} \qquad \text{Equation 4.1}$$

In this research, four sets of comparisons were made:

- Set 1: Comparison of the five main factors (i.e., pavement current condition, current traffic volume, initial cost, long-term performance benefit, and life-cycle cost) as to their influence on the priority of an M&R project. This required 10 pairwise comparisons.
- Set 2: Comparison of the six sub-factors under pavement current condition for rehabilitation projects (i.e., CS, CSRD, RS, SKID, STRUCT, and VISUAL) as to their influence on describing a pavement's current condition. This required 15 pairwise comparisons.
- Set 3: Comparison of the five sub-factors under pavement current condition for maintenance projects (i.e., DS, CSRD, RS, SKID, and VISUAL) as to their influence on describing a pavement's current condition. This required 10 pairwise comparisons.
- Set 4: Comparison of the two sub-factors under current traffic volume (i.e., AADT and TAADT) as to their influence in describing a project's traffic volume. This required one pairwise comparison.

Thus, the hierarchy shown in Figure 4.2 requires 36 comparisons in total.

4.3.2 On-Line Survey of Pairwise Comparisons of the Decision Factors

The purpose of the on-line survey was to elicit importance weights for the multiple decision factors from TxDOT district engineers and pavement managers using the AHP. This required district engineers to perform the 36 pairwise comparisons detailed above. The survey was disseminated to TxDOT's 25 districts. Twenty-seven individuals from 17 districts responded to the survey, representing 68 percent district response rate. The positions held by the respondents include director of maintenance, maintenance engineer, director of operations, maintenance supervisor, district pavement engineer, design engineer, transportation specialist, director of construction, engineering specialist, transportation engineer, director of TP&D, area engineer, and pavement/materials engineer.

In each pairwise comparison, the decision maker assigns a numerical value to the dominant factor that reflects its importance over the other. Table 4.1 shows the judgment scale used in the survey while Figure 4.3 shows a sample screenshot of a portion of the survey with actual responses from TxDOT district staff. In this example, five decision factors (i.e., DS, CSRD, RS, SKID, and VISUAL) were compared, one pair at the time, as to their influence on determining pavement current condition for maintenance projects. In this example, the respondent judged that distress score has "somewhat greater importance" over rate of deterioration in describing pavement current condition as seen in the first pair. Likewise, the district's visual assessment was deemed to have "very strong importance" over rate of deterioration.

Table 4.1 Judgment Scale in AHP

Value	Meaning
1	Equal Importance
3	Somewhat Greater Importance
5	Strong Importance
7	Very Strong Importance
9	Absolute Importance
2,4,6,8	Intermediate

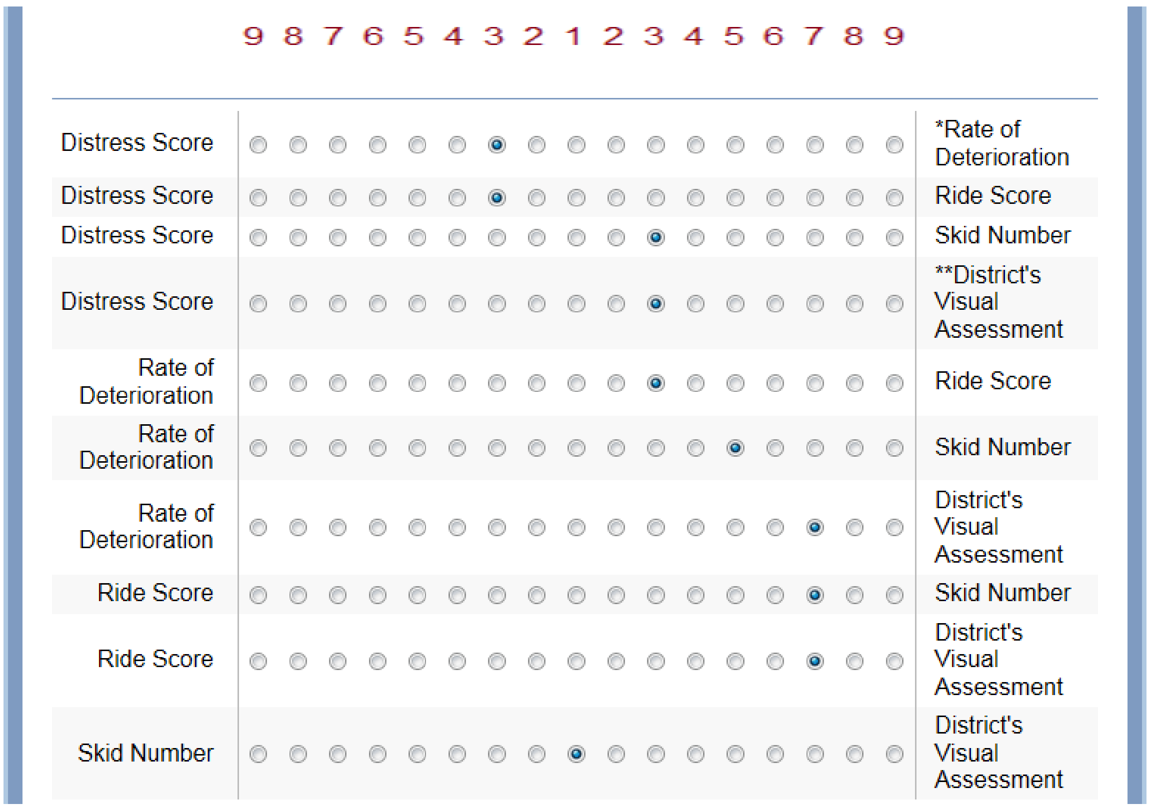


Figure 4.3 Partial Screenshot of the On-Line Survey

4.3.3 Aggregating Individual Responses into Group Response

The 27 individual responses were aggregated to derive group response, as follows:

- State-Wide: All responses received from 17 districts

- Rural Districts: Amarillo, Brownwood, Childress, Lufkin, Odessa, Paris, Wichita Falls, and Yoakum.
- Urban Districts: Beaumont, Bryan, Lubbock, Pharr, and Tyler.
- Metro Districts: Austin, Fort Worth, Houston, and San Antonio.

The individual responses were grouped into an overall group (consisting of all 27 responses), a rural group (consisting of responding rural districts), an urban group (consisting of responding urban districts) and a metro group (consisting of responding metro districts).

The group response was computed as the geometric mean of the individual pairwise ratings. Mathematically, the group pairwise ratings are computed using Equation 4.2 where G is the geometric mean of the pairwise ratings (i.e., representing state-wide response); x_i is the pairwise rating of the ith respondent, and m is the total number of responses to be aggregated (Saaty 1980):

$$G = \sqrt[m]{x_1 x_2 x_3 \ldots x_m} \qquad \text{Equation 4.2}$$

The group response were then entered into an *nxn* matrix, one for each set of comparison (see section 4.3.1) where *n* is the number of decision factors within the set. This facilitates the computation of the respective priority vectors (i.e., weights) of the decision factor in hand. Figure 4.4 illustrates this process for the state-wide group.

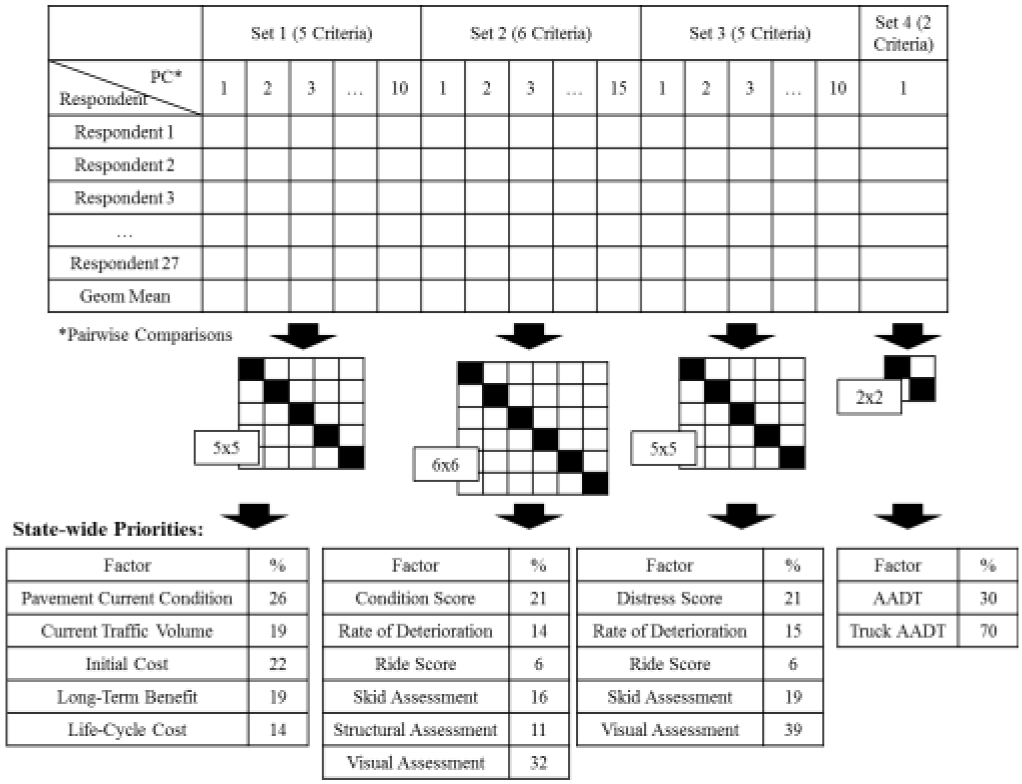


Figure 4.4 Deriving Weights from Aggregated Individual Responses

For example, the values in Table 4.2 are the geometric mean of the pairwise ratings obtained from all responses (i.e., state-wide group) for the upper-level in the hierarchy of decision factors (set 1). For example, the entry "1.89" in the "CC" row and "CTV" column means that the geometric mean of the 27 individual responses in the Pavement Current Condition-Current Traffic Volume pair is equal to 1.89. This suggests that for the state-wide group, pavement current condition (row factor) has an importance that is between "equal importance" and "somewhat greater importance" over current traffic volume (column factor). This explains the "1"s in the diagonal which means that a criterion has equal importance when compared to itself. Moreover, it was shown that for this set, 10 comparisons were made. These are represented by the 10 entries in the upper triangle of the matrix. The entries in the lower triangle are simply the reciprocal of the entries in the upper triangle. That is, the entry “0.53” in the “CTV” row and “CC” column is simply 1/1.89.

Table 4.2 Matrix of Pairwise Ratings for Set 1 (Upper-Level Decision Factors)

	CC	CTV	IC	LTPB	LCC
CC	1.00	1.89	0.97	1.22	1.87
CTV	0.53	1.00	0.76	1.41	1.38
IC	1.03	1.32	1.00	1.21	1.18
LTPB	0.82	0.71	0.83	1.00	1.50
LCC	0.53	0.72	0.85	0.67	1.00

4.3.4 Calculation of Priority Vectors

The weights of the decision factors are determined using the eigenvector method proposed by Saaty (1980). In this method the weights are computed as the normalized maximum eigenvector of the group pairwise ratings matrix (Saaty 1980). Mathematically, the maximum eigenvalue, λ_{max}, is computed using Equation 4.3 where *A* represents the *nxn* pairwise ratings matrix; *I* is the identity matrix, and *det* is the determinant.

$$\det\left(A-\lambda_{max}I\right)=0 \qquad \text{Equation 4.3}$$

The priority vector (i.e., relative weights) is therefore the vector, *w*, which satisfies Equation 4.4.

$$Aw=\lambda_{max}w \qquad \text{Equation 4.4}$$

The computation becomes tedious when multiple matrices with large sizes are involved. In these cases, on-line tools that automate this process become useful.

An alternative approach that can be easily implemented in spreadsheets is the process of averaging over normalized columns which gives a good approximation of the priority vector (Saaty 1980). This is done by normalizing the columns (i.e., dividing the entries by the column sum as shown in Table 4.3) followed by averaging the resulting values across each row. The average values represent the weights of the decision factors. Table 4.3 illustrates this process. Table 4.4 shows the close agreement between the eigenvector method and the approximate method in terms of decisions factor weights.

Table 4.3 Normalized Pairwise Ratings and Priority Vector

	CC	CTV	IC	LTPB	LCC	Priority Vector
CC	0.26	0.34	0.22	0.22	0.27	0.26
CTV	0.14	0.18	0.17	0.26	0.20	0.19
IC	0.26	0.23	0.23	0.22	0.17	0.22
LTPB	0.21	0.13	0.19	0.18	0.22	0.19
LCC	0.14	0.13	0.19	0.12	0.14	0.14
Sum	1.00	1.00	1.00	1.00	1.00	1.00

Table 4.4 Weights Computed by the Eigenvector and Approximate Methods

Decision Factor	Eigenvector	Approximate
Pavement Current Condition	0.2614	0.2608
Current Traffic Volume	0.1879	0.1882
Initial Cost	0.2230	0.2227
Long-Term Performance Benefit	0.1836	0.1839
Life-Cycle Cost	0.1441	0.1444

4.3.5 Consistency of Pairwise Ratings

In AHP, it is important to check the pair-wise comparisons for consistency. That is, if the respondent rates factor A as more important than factor B and factor B as more important than factor C, then the respondent must logically rate factor A as more important than factor C. Likewise, if factor A was rated as "absolutely more important" than factor C and factor B as "absolutely more important" than C, then factors A and B must have equal importance. However, human nature suggests that this level of perfect consistency is difficult to attain. Hence, AHP introduces a consistency ratio (CR), a measure of consistency, where a value of zero means perfectly consistent pairwise ratings. The consistency ratio, *CR*, is computed by first calculating the consistency index, *CI*, using Equation 4.5 where λ_{max} is the maximum eigenvalue and n is the size of the pairwise comparisons matrix.

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad \text{Equation 4.5}$$

CR is then computed using Equation 4.6 where *RI* is the random index. The random index is the consistency index of a randomly generated reciprocal matrix from the 1-9 scale with reciprocals forced. Average RIs for matrices with sizes, n, equal to 1-15 are provided by Saaty (1980) and are shown in Table 4.5. AHP allows a maximum acceptable CR of 10% (Saaty 1980).

$$CR = \frac{CI}{RI} \qquad \text{Equation 4.6}$$

Table 4.5 Random Indexes for Different Matrix Sizes

n	*RI*	*n*	*RI*	*n*	*RI*
1	0.00	6	1.24	11	1.51
2	0.00	7	1.32	12	1.48
3	0.58	8	1.41	13	1.56
4	0.90	9	1.45	14	1.57
5	1.12	10	1.49	15	1.59

Using the eigenvector method, λ_{max} is calculated to be 5.0747. For the approximate solution, λ_{max} is computed by summing the products of the weights and their respective column sum (see Table 4.6).

Table 4.6 Calculating λ_{max} by the Approximate Method

	CC	CTV	IC	LTPB	LCC	Priority Vector	Priority x Column Sum
CC	1.00	1.89	0.97	1.22	1.87	0.2608	1.0197
CTV	0.53	1.00	0.76	1.41	1.38	0.1882	1.0614
IC	1.03	1.32	1.00	1.21	1.18	0.2227	0.9799
LTPB	0.82	0.71	0.83	1.00	1.50	0.1839	1.0151
LCC	0.53	0.72	0.85	0.67	1.00	0.1444	1.0021
Sum	3.91	5.64	4.40	5.52	6.94		λ_{max} = 5.0782

Table 4.7 shows the consistency ratios of the four pairwise comparisons matrices for the state-wide, rural, urban, and metro groups. All CR values fall within the allowable limit suggesting consistency of the aggregated group responses.

Table 4.7 Consistency Ratios of Pairwise Comparison Matrices

Matrix	CR (%)			
	State-wide	Rural	Urban	Metro
Set 1 (5x5)	1.7	1.3	1.1	7.8
Set 2 (6x6)	2.6	2.2	5.8	5.2
Set 3 (5x5)	1.9	3.3	5.1	3.0
Set 4 (2x2)	NA	NA	NA	NA

The procedure explained above was applied to all pairwise comparison matrices to determine the priority weights of the decision factors for each group of responses. The results are presented and discussed in the following sections.

4.3.6 State-Wide Priority Weights

Figure 4.5 shows that pavement current condition is the top criterion considered in prioritizing pavement M&R projects. This is followed by initial cost and a tie between current traffic volume and long-term performance benefit. Note that the top criteria are the short-term factors while the bottom criteria are those associated with a long-term M&R approach.

Figures 4.6 and 4.7 show the weights of the sub-factors that represent pavement current condition for rehabilitation and maintenance projects, respectively. As can be observed, the weights and the order of priority of factors for both cases are very much alike. Visual assessment is the top consideration for both cases, followed by a pavement condition index: CS for rehabilitation projects and DS for maintenance projects. Ride score received the least weight for both cases. This implies that TxDOT has the option to use separate weights for maintenance and rehabilitation, or to combine the two to generate common weights for both rehabilitation and maintenance projects.

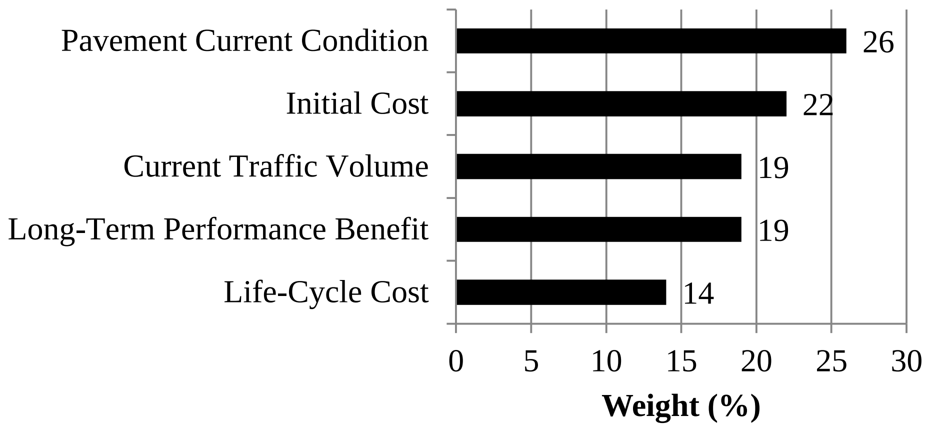


Figure 4.5 Weights of Upper-Level Factors

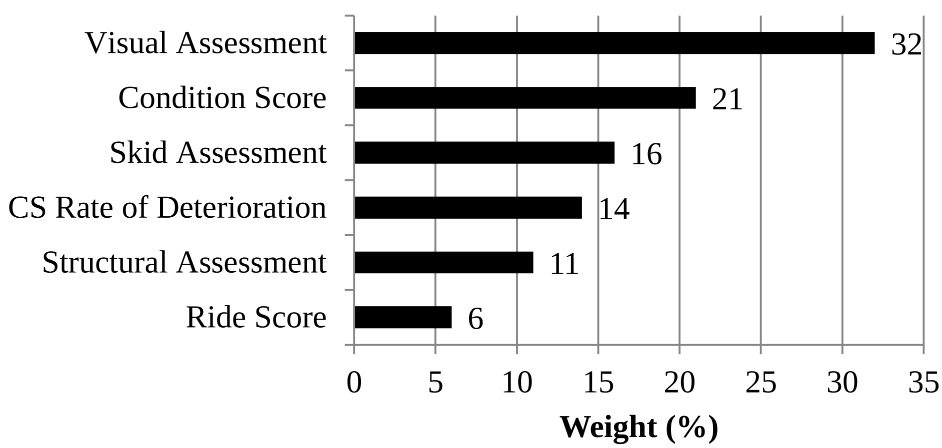


Figure 4.6 Weights of Current Condition Factors (Rehabilitation)

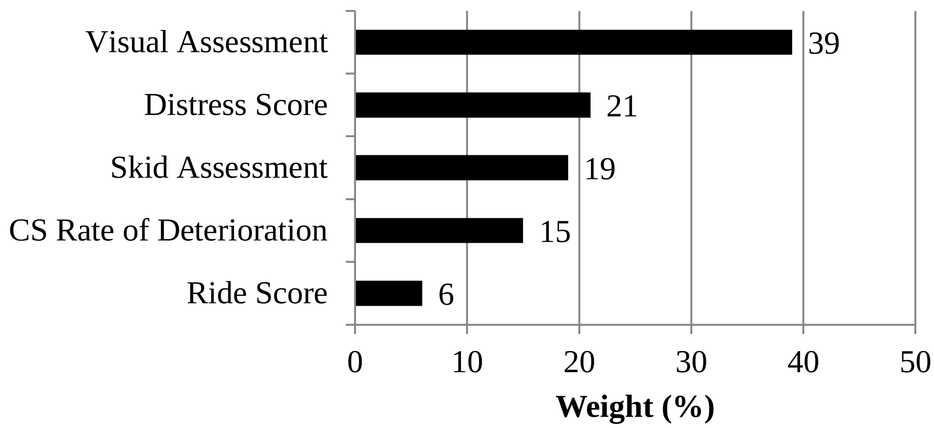


Figure 4.7 Weights of Current Condition Factors (Maintenance)

The importance weights of AADT versus Truck AADT are shown in Figure 4.8 where the latter dominates the former. Since truck AADT also reflects the economic importance of a roadway corridor, it can be said that the respondents take this matter into consideration in prioritizing pavement M&R projects.

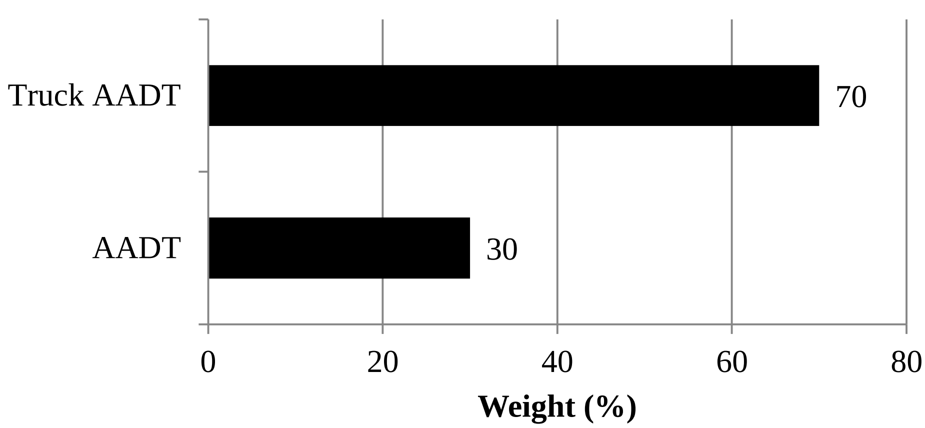


Figure 4.8 Weights of Current Traffic Volume Factors

4.3.7 Priority Weights by District Type

As discussed earlier, the responses were aggregated based on district type (i.e., rural, urban, and metro) to determine if the priority weights vary among these groups. The results are shown in Figures 4.9 through 4.12. The following observations can be made based on these results:

- Short and Long-term Categories of Factors (Figure 4.9):
    - The order of priority for urban, rural, and all districts combined is fairly similar (with minor exceptions). However, the magnitudes of the weights vary.
    - For urban and rural districts, pavement current condition and M&R initial cost are the top influencing factors (among factors considered in this study).
    - The order of priority and magnitude of the weights for metro districts are markedly different from those for the other districts.
    - For metro districts, long-term-performance benefits, initial cost, and current traffic volume are the top priorities.
- Factors representing pavement current condition (Figures 4.10 and 4.11)
    - District's own visual assessment is the top indicator of pavement current condition for both urban and rural districts. It is followed by distress and condition scores, and to a lesser extent skid resistance.
    - Skid resistance is the top indicator of pavement current condition for metro districts.

- ○ All district types (rural, urban, and metro) consistently assigned the least weight to ride score as an indicator of pavement current condition.

- Factors representing current traffic volume (Figure 12)
  - ○ All types of districts agree in giving truck AADT higher weight than AADT.

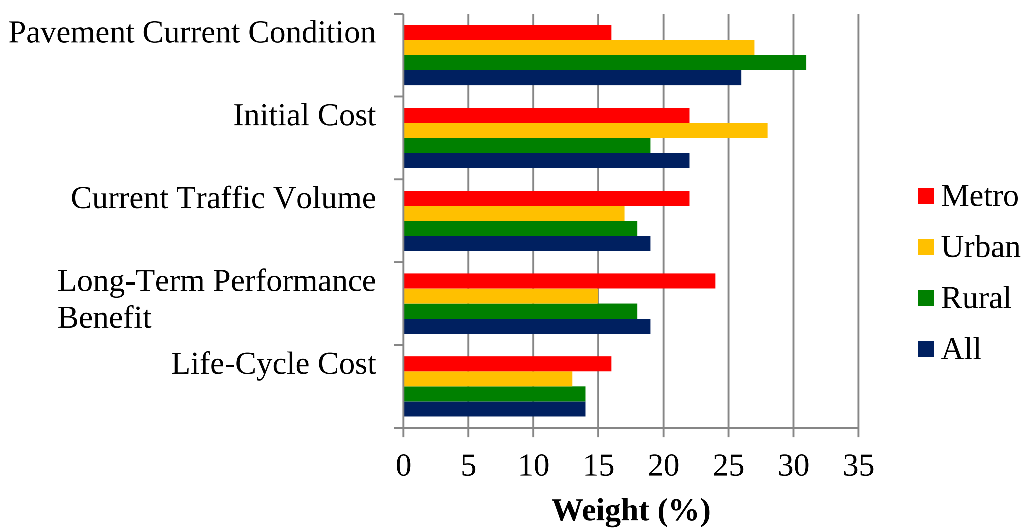


Figure 4.9 Priority Weights of the Upper-Level Factors by District Type

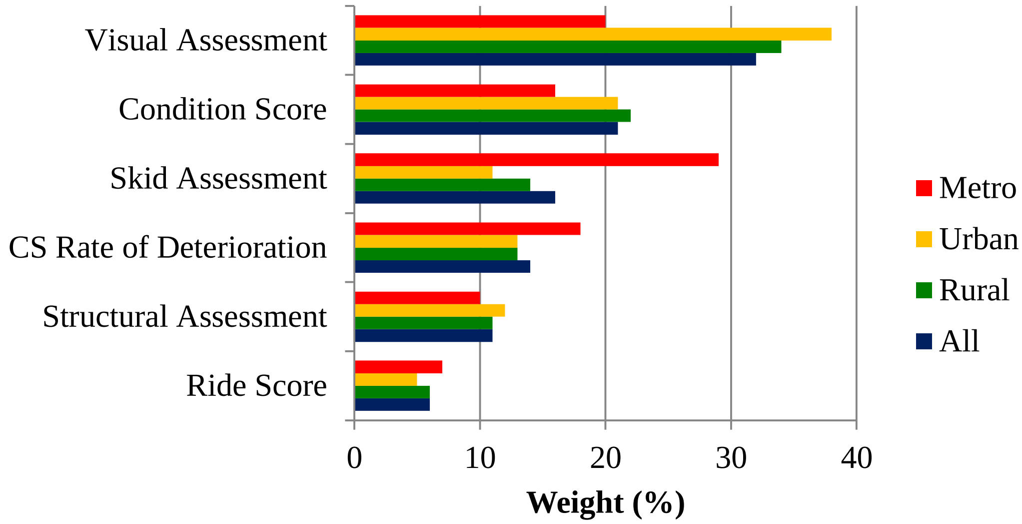


Figure 4.10 Priority Weights of Current Condition Factors (Rehab) by District Type

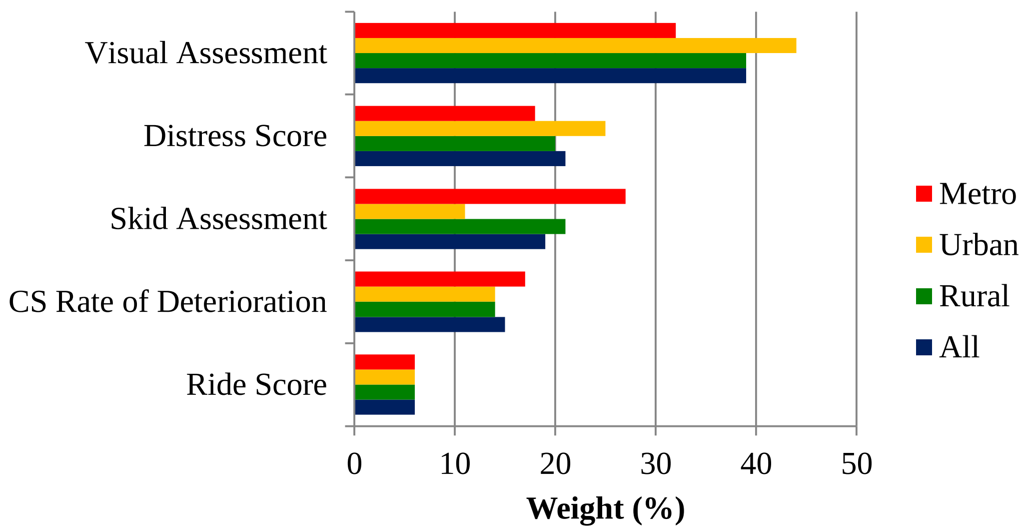


Figure 4.11 Priority Weights of Current Condition Factors (Maintenance) by District Type

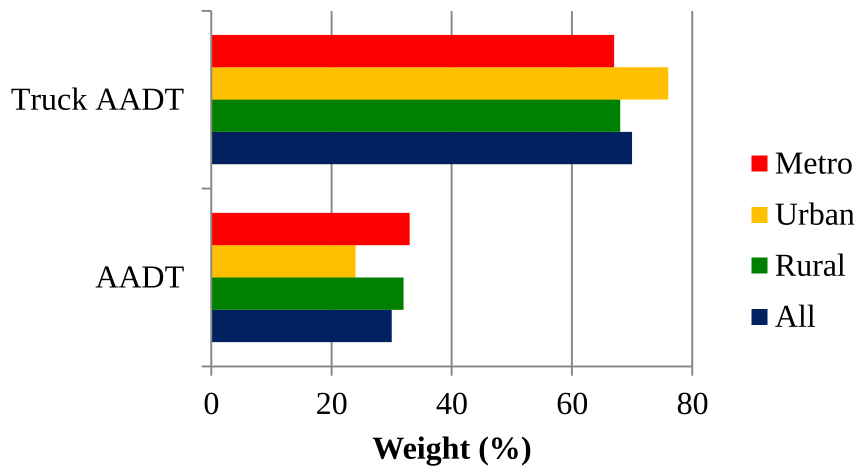


Figure 4.12 Priority Weights of Current Traffic Volume Factors by District Type

4.3.8 Summary of Priority Weights

A summary of the priority weights (i.e., global weights) for the factors considered in the online survey are provided in Tables 4.8 through 4.11, for all districts combined, rural districts, urban districts, and metro districts. These results suggest that there are differences in M&R priorities of the decision makers in these district types. Thus, it would be prudent to enable different district types (or individual districts) to use different priority weights. The weights provided in this study should be considered as default values (or reference points) for TxDOT's districts.

Table 4.8 Priority Weights Computed using All Responses

Key Decision Factors	Weight,%
Pavement Current Condition	26
Visual Assessment ($Weight^R$ = 8.3%, $Weight^M$ = 10.1%)	
Condition Score ($Weight^R$ = 5.5%)	
Distress Score ($Weight^M$ = 5.5%)	
Skid Assessment ($Weight^R$ = 4.2%, $Weight^M$ = 4.9%)	
CS Rate of Deterioration ($Weight^R$ = 3.6%, $Weight^M$ = 3.9%)	
Structural Assessment ($Weight^R$ = 2.9%)	
Ride Score ($Weight^R$ = 1.6%, $Weight^M$ = 1.6%)	
Current Traffic Volume	19
Truck AADT (Weight = 13.3%)	
AADT (Weight = 5.7%)	
Initial Cost	22
Long-Term Performance Benefits	19
Life-Cycle Cost	14
Total:	100

R=Rehabilitation, M=Maintenance

Table 4.9 Priority Weights Computed using Rural District Responses

Key Decision Factors	Weight,%
Pavement Current Condition	31
Visual Assessment ($Weight^R$ = 10.5%, $Weight^M$ = 12.1%)	
Condition Score ($Weight^R$ = 6.8%)	
Distress Score ($Weight^M$ = 6.2%)	
Skid Assessment ($Weight^R$ = 4.3%, $Weight^M$ = 6.5%)	
CS Rate of Deterioration ($Weight^R$ = 4.0%, $Weight^M$ = 4.3%)	
Structural Assessment ($Weight^R$ = 3.4%)	
Ride Score ($Weight^R$ = 1.9%, $Weight^M$ = 1.9%)	
Current Traffic Volume	18
Truck AADT (Weight = 12.2%)	
AADT (Weight = 5.8%)	
Initial Cost	19
Long-Term Performance Benefits	18
Life-Cycle Cost	14
Total:	100

R=Rehabilitation, M=Maintenance

Table 4.10 Priority Weights Computed using Urban District Responses

Key Decision Factors	Weight,%
Pavement Current Condition	27
Visual Assessment ($Weight^R$ = 10.3%, $Weight^M$ = 11.9%)	
Condition Score ($Weight^R$ = 5.7%)	
Distress Score ($Weight^M$ = 6.8%)	
Skid Assessment ($Weight^R$ = 3.0%, $Weight^M$ = 3.0%)	
CS Rate of Deterioration ($Weight^R$ = 3.5%, $Weight^M$ = 3.8%)	
Structural Assessment ($Weight^R$ = 3.2%)	
Ride Score ($Weight^R$ = 1.4%, $Weight^M$ = 1.6%)	
Current Traffic Volume	17
Truck AADT (Weight = 12.9%)	
AADT (Weight = 4.1%)	
Initial Cost	28
Long-Term Performance Benefits	15
Life-Cycle Cost	13
Total:	100

R=Rehabilitation, M=Maintenance

Table 4.11 Priority Weights Computed using Metro District Responses

Key Decision Factors	Weight,%
Pavement Current Condition	16
Visual Assessment ($Weight^R$ = 3.2%, $Weight^M$ = 5.1%)	
Condition Score ($Weight^R$ = 2.6%)	
Distress Score ($Weight^M$ = 2.9%)	
Skid Assessment ($Weight^R$ = 4.6%, $Weight^M$ = 4.3%)	
CS Rate of Deterioration ($Weight^R$ = 2.9%, $Weight^M$ = 2.7%)	
Structural Assessment ($Weight^R$ = 1.6%)	
Ride Score ($Weight^R$ = 1.1%, $Weight^M$ = 1.0%)	
Current Traffic Volume	22
Truck AADT (Weight = 14.7%)	
AADT (Weight = 7.3%)	
Initial Cost	22
Long-Term Performance Benefits	24
Life-Cycle Cost	16
Total:	100

R=Rehabilitation, M=Maintenance

5. PRIORITIZATION OF M&R PROJECTS FOR MULTI-YEAR PAVEMENT MANAGEMENT PLANS

Once potential M&R projects are formed using either the CDA or PDA approach, they are prioritized based on multiple decision factors throughout a multi-year planning period. This section of the thesis details this process, including the development of a prioritization index, the optimization technique used to select the optimum set of projects under budgetary constraint, and performance prediction models. The overall methodology in which these analytical techniques and models are integrated to generate a multi-year PMP is discussed first.

5.1 Overview of the PMP Methodology

The developed methodology for preparing a multi-year pavement management plan is illustrated in Figure 5.1.

The algorithm first groups the data collection sections into segments using either the CDA or PDA approach. In addition to the pavement attributes (i.e., CS, DS, etc.) found in the PMIS, districts may also enter additional condition assessments (i.e., skid assessment, structural assessment, and visual assessment) as well as projects that the district commits to fund (forced projects).

For every segment formed, the algorithm compares its CS or DS to an M&R trigger value. Groups with CS or DS below the trigger value are considered to be candidate projects for M&R while no intervention is needed for those with CS or DS above the trigger value. For each candidate project, the viable M&R treatment alternatives are identified and their long-term performance benefit and life-cycle cost are computed using derived performance prediction models. Each M&R alternative is also assigned a priority score that is computed based on a number of decision factors.

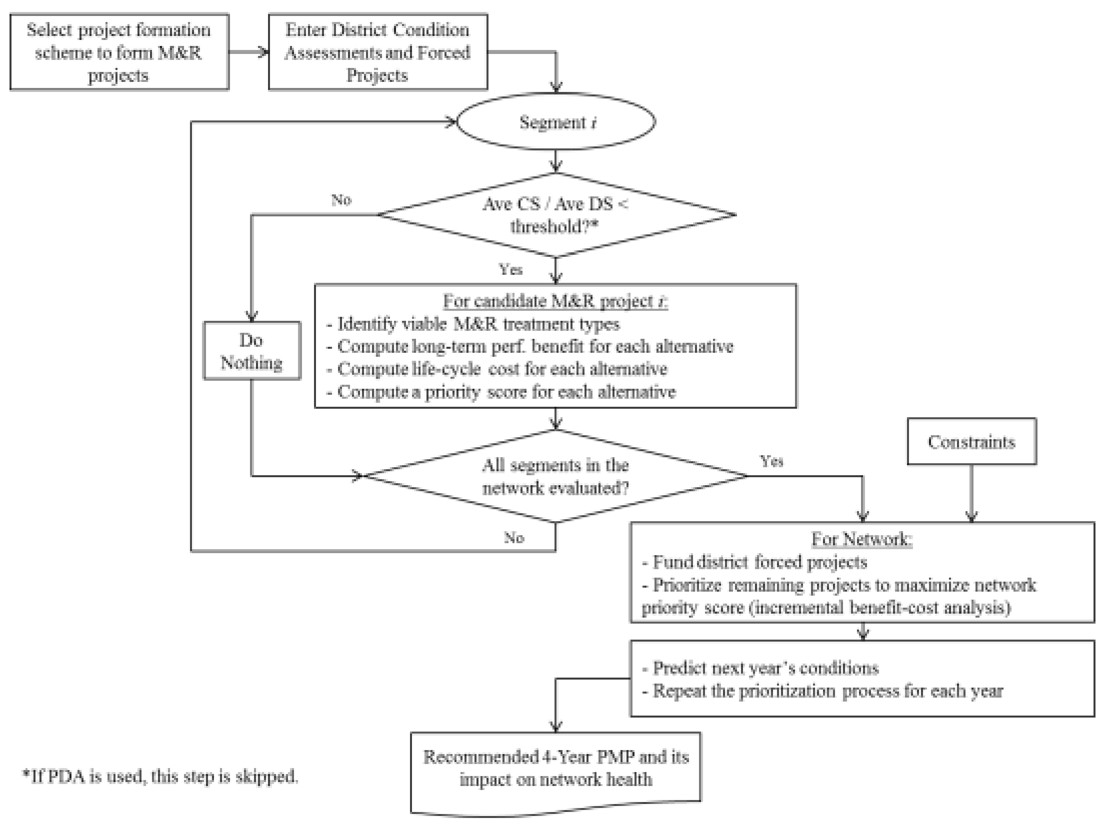


Figure 5.1 Methodological Framework for Developing the PMP

The candidate projects are then prioritized using the Incremental Benefit-Cost (IBC) algorithm to generate a list of projects that maximizes the total priority score for a given budget. The network's condition is then projected for the following year, and the process is repeated every year until the end of the planning horizon (i.e., four years). Each year's list of M&R projects constitute the four-year PMP and its impact on the network condition is analyzed.

5.2 Performance Prediction Models

Performance prediction models are essential for multi-year planning and programming of pavement M&R activities. Models for predicting DS, CS, and RS were derived from distress prediction models that have been recently calibrated by TxDOT (Gharaibeh et al. 2012). The other performance indicators considered in the PMP methodology (i.e., CSRD, SKID, STRUCT, and VISUAL) are used to prioritize projects for the current year only since no models are available for projecting these indicators into the future. Thus, their future values are set to "NULL"; indicating that they are not used for prioritizing M&R projects beyond the first year of the PMP plan.

Equations 5.1 to 5.3 are used for computing DS and CS. These equations were developed for Texas in the 1990s (Stampley et al. 1995).

$$U_i = \begin{cases} 1.0 & when\ L_i = 0 \\ 1 - \alpha e^{-\left(\frac{\rho}{L_i}\right)^{\beta}} & when\ L_i > 0 \end{cases} \qquad \text{Equation 5.1}$$

$$DS = 100 \times \prod_{i=1}^{n} U_i \qquad \text{Equation 5.2}$$

$$CS = U_{Ride} \times DS \qquad \text{Equation 5.3}$$

L_i is the density of individual distress types in the pavement section. Distress density (L_i) is expressed as quantity of distress per mile, quantity of distress per section area, quantity of distress per 100-ft, etc., depending on the distress type. For asphalt pavements, for example, eight distress types are considered—shallow rutting, deep rutting, failures, block cracking, alligator cracking, longitudinal cracking, transverse cracking, and patching. Ride L_i represents the percent of ride quality lost over time. U_i is a utility value (ranging between zero and 1.0) and represents the quality of a pavement in terms of overall usefulness (e.g., a U_i of 1.0 indicates that distress type *i* is not present and thus is most useful). Coefficients α (maximum loss factor), β (slope factor), and ρ (prolongation factor) control the location of the utility curve's inflection point and the slope of the curve at that point. As discussed earlier, *DS* is the Distress Score, which is a composite index that combines multiple L_i*'s* using mathematical utility functions. DS has a 1–100 scale (with 100 representing no or minimal distress). *CS* is the Condition Score, which is a broad composite index that combines DS and ride quality. CS has a 1–100 scale (with 100 representing no or minimal distress and roughness).

To derive models for predicting DS, CS, and RS, TxDOT's most updated performance prediction models were used. These models were calibrated in TxDOT Project 0-6386 based on actual field performance data (Gharaibeh et al. 2012). They predict the densities of individual distress types and loss of ride quality over time (i.e., pavement age) using a sigmoidal curve (S-curve) and are expressed as shown in Equation 5.4 below:

$$L_i = \begin{cases} 0 & when\ Age = 0 \\ \alpha_i e^{-\left(\frac{A_i}{Age}\right)^{\beta_i}} & when\ Age > 0 \end{cases} \qquad \text{Equation 5.4}$$

In Equation 5.4, *Age* is the number of years since last construction or M&R applied to the pavement. α_i is the maximum loss factor that controls the maximum L_i. β_i is the slope factor which controls how steeply L_i increases in the middle of the curve. A_i is the prolongation factor that controls the location of the L_i curve's inflection point. These model factors vary for different combinations of traffic, climate, and subgrade conditions. Figure 5.2 illustrates the general shape of this curve.

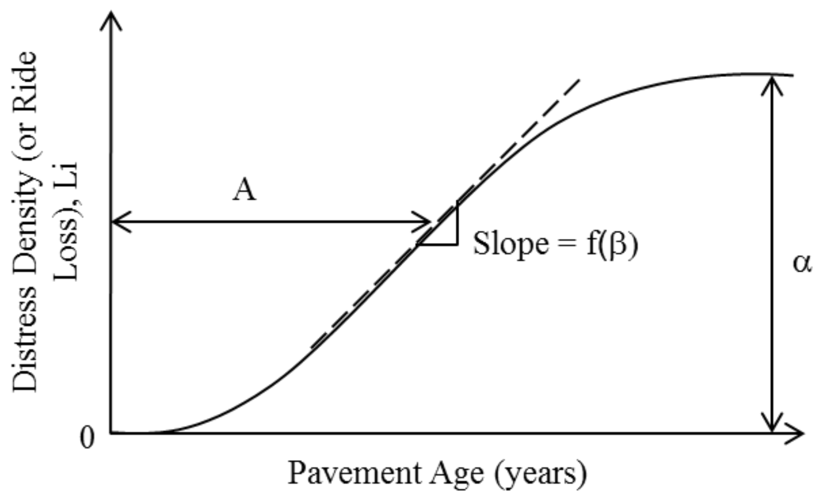


Figure 5.2 Typical L_i Prediction Curve

To derive prediction models for DS and CS, the L_i vs. age models were converted to U_i vs. age models through the L_i vs. U_i equation (see Equation 5.1). Each considered distress has its own U_i vs. age curve. Since DS at any given time is simply the product of 100 and the utility values of all distresses present (see Equation 5.2), then a DS vs. age curve was derived from the individual utility curves as shown in Figure 5.3.

Finally, a CS vs. age curve was derived by combining the DS curve with the utility curve for ride quality (according to Equation 5.3) as shown in Figure 5.4.

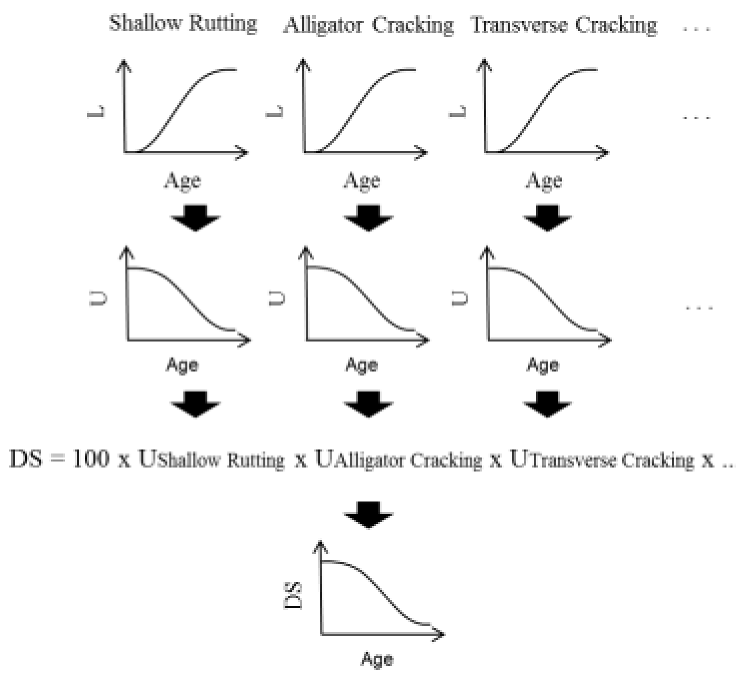


Figure 5.3 Derivation of DS Prediction Models

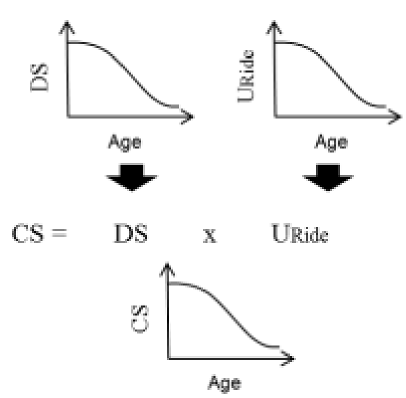


Figure 5.4 Derivation of CS Prediction Models

The DS vs. age and CS vs. age curves take the form of a sigmoidal curve and are mathematically expressed in Equations 5.5 and 5.6, respectively. In these equations, DS_0 and CS_0 are the DS and CS immediately after construction/M&R respectively; *Age* is the number of years since last construction/M&R; β is the slope factor; and ρ is the prolongation factor.

$$DS = DS_0 \left[1 - e^{-\left(\frac{\rho}{AGE}\right)^{\beta}} \right] \quad \text{Equation 5.5}$$

$$CS = CS_0 \left[1 - e^{-\left(\frac{\rho}{AGE}\right)^{\beta}} \right] \quad \text{Equation 5.6}$$

The β and ρ were derived for different combinations of climate-subgrade zone, pavement family, ESAL class, traffic class (AADT × Speed), and M&R type. These groups are defined in great detail in the final report of TxDOT Project 0-6386 (Gharaibeh et al. 2012). Figures 5.5 and 5.6 show the different combinations for which DS and CS models were developed. The β and ρ values for Zone 2 (wet-warm climate, and poor, very poor, or mixed subgrade) are shown in Tables 5.1 and 5.2 for DS and CS, respectively.

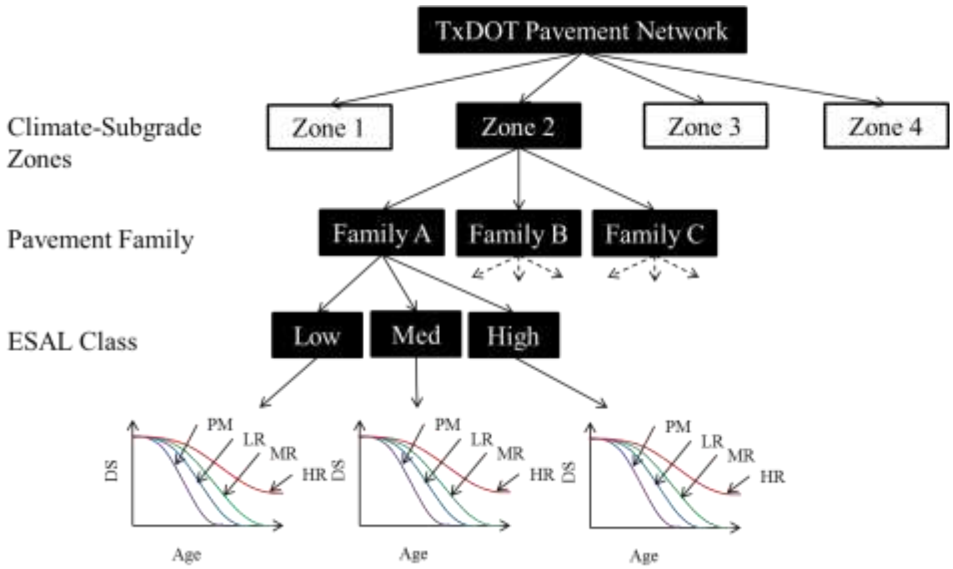


Figure 5.5 Pavement Family-ESAL Class-Treatment Type Combinations for DS Models

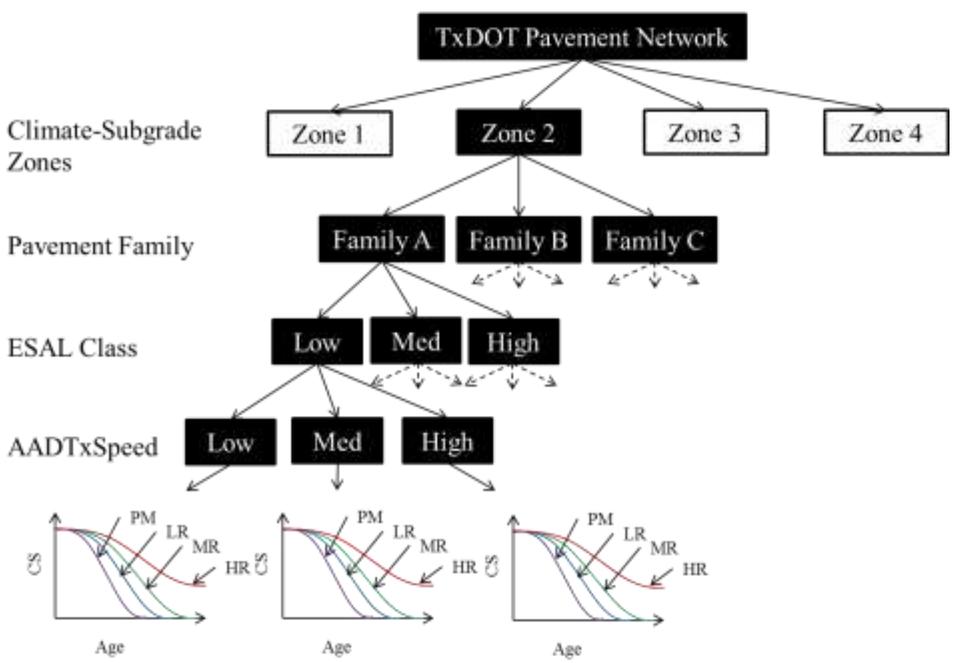


Figure 5.6 Pavement Family-ESAL Class-Traffic Class-Treatment Type Combinations for CS Models

Table 5.1 Rho and Beta Coefficients for DS Prediction Models for Climate-Subgrade Zone 2

Pavement Family-ESAL Class	PM		LR		MR		HR	
	ρ	β	ρ	β	ρ	β	ρ	β
A-Low	9.3	2.3	11	2.3	12.9	2.4	16.1	2.6
A-Med	8.9	1.3	12.5	1.4	14.8	1.5	19.3	1.6
A-High	10.5	1.5	12.5	1.3	14.9	1.1	16.5	1.2
B-Low	9	3	10.2	3.3	12.1	4	14.4	4.6
B-Med	11.9	2.4	13.4	2.3	14.4	2.3	15.4	2.4
B-High	11.9	2.4	13.4	2.3	14.4	2.3	15.4	2.4
C-Low	14.1	2.1	17	2.4	21.4	2.6	25.2	2.3
C-Med	11.4	1.2	17.4	1.3	21.7	1.5	29.3	1.5
C-High	11.4	1.2	17.4	1.3	21.7	1.5	29.3	1.5

Table 5.2 Rho and Beta Coefficients for CS Prediction Models for Climate-Subgrade Zone 2

Pavement Family-ESAL-Traffic Class	PM		LR		MR		HR	
	ρ	β	ρ	β	ρ	β	ρ	β
A-Low-Low	7.5	4.7	10.9	2.4	12.9	2.4	16.2	2.5
A-Low-Med	7	9.3	10.8	2.5	12.9	2.4	16.2	2.5
A-Low-High	6.9	10.7	10.6	2.7	12.9	2.4	16.2	2.5
A-Med-Low	6.1	4.4	8.4	10	11.5	3.4	13.5	11.1
A-Med-Med	6	62.2	8.1	85.6	11.3	17.6	13.3	28.4
A-Med-High	6	62.2	8.1	85.6	11.2	21.4	13.2	33.8
A-High-Low	6.5	5.4	8.3	8.3	10	6.8	14.8	1.6
A-High-Med	6.1	62.7	8.1	32.2	10.1	32.7	14.8	1.6
A-High-High	6.1	62.7	8.1	74	10.1	55	14.8	1.6
B-Low-Low	6.6	5.9	7.7	7.4	9.9	9.7	13.2	15
B-Low-Med	6.2	37	7.3	28.8	9.5	28.6	13	40.6
B-Low-High	6.1	73.1	7.1	86.6	9.4	34	13	73.3
B-Med-Low	8.2	5.3	14.2	2.1	14.4	2.3	15.2	2.6
B-Med-Med	7.5	11.9	14.1	2.1	14.4	2.3	15.2	2.6
B-Med-High	7.3	13.5	14	2.1	14.4	2.3	15.2	2.6
B-High-Low	8.2	5.3	14.2	2.1	14.4	2.3	15.2	2.6
B-High-Med	7.5	11.9	14.1	2.1	14.4	2.3	15.2	2.6
B-High-High	7.3	13.5	14	2.1	14.4	2.3	15.2	2.6
C-Low-Low	7.1	4	8.4	5.3	11	6.8	13.1	7.2
C-Low-Med	6.4	15.2	7.7	16.2	10.1	15	12.3	20.3
C-Low-High	6.3	17.2	7.8	34.8	10	18.3	12.2	23.7
C-Med-Low	6.1	3.4	9	6.8	11.5	9.4	27.2	1.7
C-Med-Med	5.6	10.2	8.5	14.2	11	19.9	19.3	38.4
C-Med-High	5.5	11.6	8.3	16.5	10.9	26	19.3	46.4
C-High-Low	6.1	3.4	9	6.8	11.5	9.4	27.2	1.7
C-High-Med	5.6	10.2	8.5	14.2	11	19.9	19.3	38.4
C-High-High	5.5	11.6	8.3	16.5	10.9	26	19.3	46.4

5.3 Identifying Viable M&R Treatment Alternatives

After the network is segmented (i.e., data collection sections are grouped into longer roadway segments), segments that need M&R are identified based on a CS or DS trigger value defined by the agency. In this study, a CS trigger value of 80 is used. That is, segments with CS < 80 are identified as candidate M&R project and compete for available funding. Note that while TxDOT aims for 90% of its roads to have CS values greater than or equal to 70 (threshold for good condition), the trigger value is set 10 points higher. This was done to guard against pavements that are approaching the threshold and might fall below it within a short time (e.g., less than a year).

For each segment that is identified as a candidate M&R project, four possible M&R treatment types are evaluated: (1) Preventive Maintenance; (2) Light Rehabilitation; (3) Medium Rehabilitation; and (4) Heavy Rehabilitation. However, depending on the project's condition, not all of the four treatment types may be viable alternatives. To determine the viability of an M&R treatment and at the same time to guard against the potential for repetitive treatments (i.e., a recently repaired project being triggered again for M&R in the following year), the following criteria were used in the proposed PMP methodology:

- Trigger + 5 Rule: In general, a treatment is counted as a viable alternative if it is able to raise the project's average CS to at least five points above the M&R trigger value (i.e., at least 85 for a CS trigger value of 80). The five-point limit was imposed to prevent repetitive M&R work on the same roadway.

The immediate gains in pavement condition due to applying the four M&R types are shown in Table 5.3 (Texas Department of Transportation 2011).

Table 5.3 Immediate Effects of Treatments on Pavement Condition

Treatment Type	Reduction in Distress Rating[1]	Gain in Ride Score
PM	Set distress L_i to zero	Increase Ride Score by 0.5[2]
LR	Set distress L_i to zero	Increase Ride Score by 1.5[2]
MR	Set distress L_i to zero	Set Ride Score to 4.8
HR	Set distress L_i to zero	Set Ride Score to 4.8

[1] L_i=0.0 and U_i = 1.0
[2] Without exceeding the maximum practical ride score value of 4.8

To compute the post-treatment CS, the post-treatment RS is converted to L_r (percent of ride quality lost) using the following Equation 5.7 (Texas Department of Transportation 2011):

For "Low" AADT × Speed Class:

$$L_r = 100x\left(\frac{2.5 - Ride\,Score}{2.5}\right) \quad \text{Equation 5.7a}$$

For "Medium" AADT × Speed Class:

$$L_r = 100x\left(\frac{3.0 - Ride\,Score}{3.0}\right) \quad \text{Equation 5.7b}$$

For "High" AADT × Speed Class:

$$L_r = 100x\left(\frac{3.5 - Ride\,Score}{3.5}\right) \quad \text{Equation 5.7c}$$

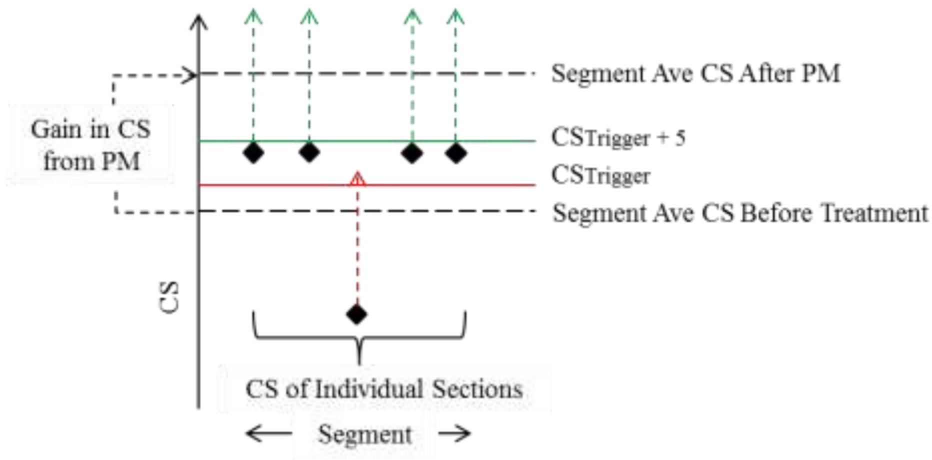
where L_r is the percent of ride quality lost (compared to perfectly smooth pavement). When calculated L_r is less than or equal to zero, L_r is set to zero.

Once the post-treatment ride score is converted to L_r, it can then be converted to a utility value (U_{Ride}) as explained previously (Equation 5.1). Finally, the post-treatment DS and U_{Ride} are combined to determine the post-treatment CS.

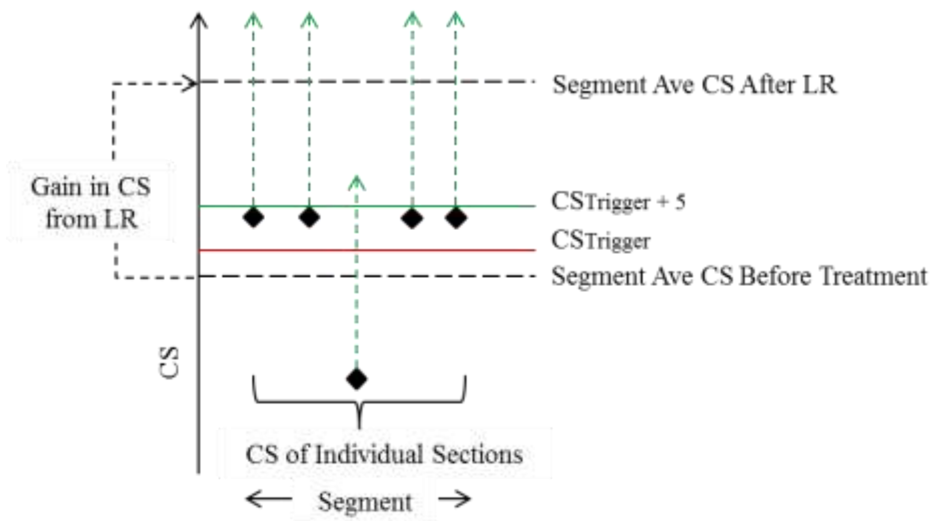
- Treatment Disqualifier: While a certain treatment may be regarded as viable based on its effect on average condition, it may still be disqualified from consideration if the minimum CS of the segment (i.e., the lowest CS among the individual data collection sections within the group) is lower than a certain value (see Figure 5.7a). Table 5.4 shows this additional condition. This is based on TxDOT CS boundary values between "Fair" and "Poor" (i.e., CS = 50) and between "Poor" and "Very Poor" (i.e., CS = 35) (Texas Department of Transportation 2011). Note that since MR and HR reset the scores to perfect condition, they would always be viable alternatives.

Table 5.4 M&R Treatment Viability Criteria Based on Group Minimum CS

Treatment Type	Condition for Inclusion as a Viable Alternative
PM	Min. individual CS of the segment ≥ 50
LR	Min. individual CS of the segment ≥ 35
MR	No restriction
HR	No restriction



(a) PM is viable on average but disqualified due to group minimum CS



(b) LR replaces PM as a viable treatment

Figure 5.7 Example of the Effect of Applying the M&R Viability Criteria Based on Group Minimum CS

While the conditions in Table 5.4 result in realistic project recommendations in the PMP (i.e. no repetitive projects), they may, on the other hand, overprovide for parts of the roadway segment that are in relatively good condition and consequently result in higher needs estimates (see Figure 5.7b). Thus, the concept of "hybrid projects" is introduced. A hybrid project consists of two M&R treatment types (e.g., a PM and LR) applied to different parts of the roadway segment according to its pavement condition. The segment in Figure 5.7, for example, qualifies as a hybrid PM/LR project where the LR performance prediction model is used to project its future performance but the project's total cost is computed using Equation 5.10, with the LR unit cost applied over one section and the PM unit cost applied over four sections. Table 5.5 explains the possible "hybrid" project types.

Table 5.5 Possible Hybrid Project Types

Designation	Applicable Performance Model	Scenarios when Used
PM/LR	LR	PM is viable based on average CS but unviable based on segment Min CS ($35 \leq$ Min CS<50)
PM/MR	MR	PM is viable based on average CS but unviable based on segment Min CS (Min CS<35)
LR/MR	MR	LR is viable based on average CS but unviable based on segment Min CS (Min CS<35)

5.4 Long-Term Performance Benefit and Life-Cycle Cost

The LTPB for each viable M&R alternative is computed using the area between the CS performance curve and an agency-defined threshold value; which is called the Area Under the Performance Curve (AUPC). This parameter quantifies the performance benefit of applying a certain M&R type by considering both the condition improvement caused by the treatment and the life of the treatment. In this research, a CS threshold value of 70 was used for AUPC computation. While the trigger value was set at CS=80 as mentioned previously, a pavement with CS of, say 75, is still “Good” and therefore still useful (i.e., with benefit). The AUPC shown in Figure 5.8 represents the benefit of applying a particular M&R treatment (i.e., PM, LR, MR, or HR). Thus, the total benefit is the sum of these areas throughout the analysis period (e.g., 20 years). This quantity is then divided by the number of years (*n*) in the analysis period (e.g., 20) and multiplied by the annual traffic (*AADT x 365)*, number of lanes (*N*), and length of the segment (*L*) to account for the effect of usage and project size on benefit, as follows:

$$AnnualBenefit = (AUPC / n) \times AADT \times 365 \times N \times L \qquad \text{Equation 5.8}$$

The annualized total benefit is the LTPB used later as one of the decision factors that influence the prioritization of projects.

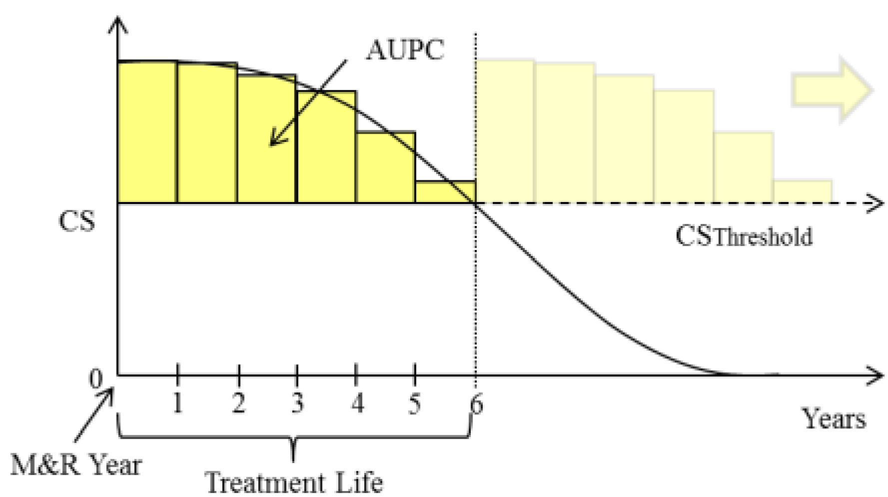


Figure 5.8 Illustration of the Area Under the Performance Curve (AUPC) Concept

The unit costs of each M&R alternative are shown in Table 5.6. These were derived from cost data of M&R projects across Texas. Hence, the treatment cost for applying M&R alternative *j* on project *i*, is given by Equation 5.9 where UC_j is the treatment unit cost; L_i is the length of project *i*; and N_i is the number of lanes.

$$Treatment\,Cost_{ij} = UC_j \; x \; L_i \; x \; N_i \qquad \text{Equation 5.9}$$

Table 5.6 M&R Treatments State-Wide Unit Cost

Treatment Type	Unit Cost ($/Lane-Mile)
PM	$14,728
LR	76,086
MR	78,429
HR	133,776

For hybrid projects, the treatment costs is to be computed using Equation 5.10 where L_i and N_i are still project length and number of lanes respectively; UC_j is the treatment unit cost of the lighter M&R treatment *j*; P_j is the proportion of project lane-miles that is repairable by treatment *j*; UC_k is the treatment unit cost of the heavier M&R alternative *k*; and P_k is the proportion of project lane-miles for which treatment *k* is applied (i.e., $P_k = 1.00 - P_j$).

$$Treatment\,Cost_{i\;j/k} = UC_j \; x \; L_i \; x \; N_i \; x \; P_j + UC_k \; x \; L_i \; x \; N_i \; x \; P_k \qquad \text{Equation 5.10}$$

Knowing the treatment life and cost of each M&R alternative, their corresponding life-cycle cost can be computed by assuming that the same M&R treatment is repeatedly applied on the pavement throughout the analysis period. Figure 5.9 illustrates an example of a cash flow of an M&R type during the analysis period.

Notice that salvage value is computed at the end of the analysis period, as shown in Equation 5.11.

$$SalvageValue = \frac{Remaining\ Life}{Treatment\ Life} xTreatment\ Cost \qquad \text{Equation 5.11}$$

The net present value of this cash flow is computed and then converted into an Equivalent Uniform Annual Cost (EUAC) stream. This represents the LCC used in subsequent computations.

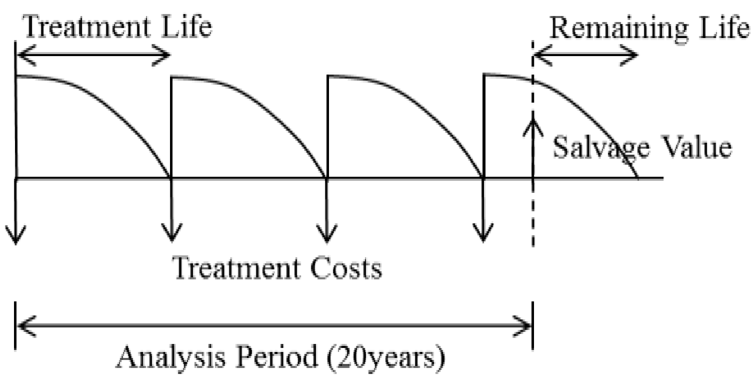


Figure 5.9 Calculating Life-Cycle Cost

5.5 Prioritization of Projects

Candidate M&R projects are prioritized based on the decision factors deemed important by TxDOT districts. These factors and their weights were discussed earlier in section four of this thesis. The units of measure (e.g., CS is unit-less, AADT is in vehicles per day, IC is in dollars) and the range of values that each variable can take (e.g., CS ranges from 0 to 100, SKID can be 0,1, or NULL, AADT ranges from 0 to tens of thousands) differ for each decision factor. Hence, these values must be converted to utility values (0 to 1) to facilitate comparison and the computation of each candidate project's priority score.

Raw values of these decision factors were converted to 0-1 utility values through linear normalization. Figure 5.10 shows the first type of decision factors where the higher the value, the lower the priority. For instance, high CS, DS, and RS values indicate good condition and thus lower need for M&R. Conversely, the second type of decision factors includes those that increase in priority as their values increase. For instance, a high CSRD suggests rapid deterioration and thus, the urgency to apply M&R is high.

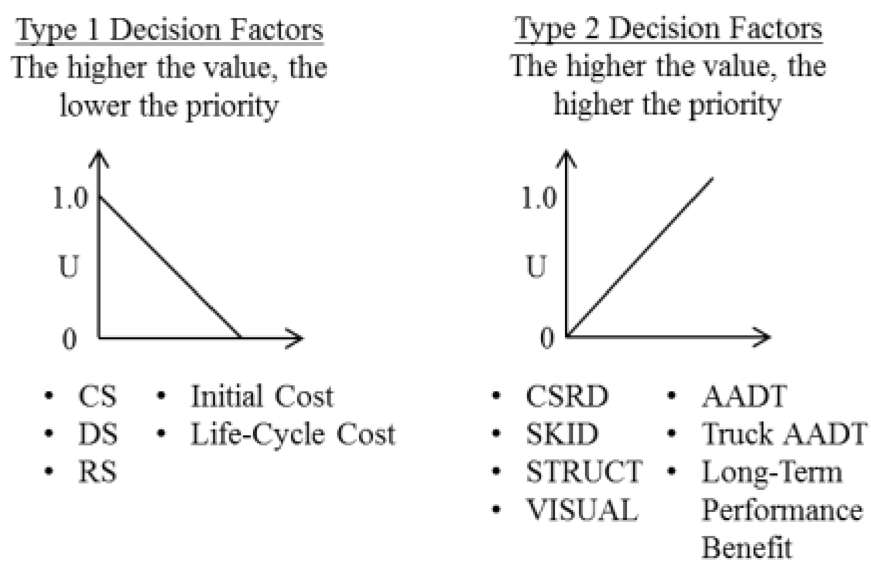


Figure 5.10 Normalization of the Values of the Decision Factors

It should be noted that forced projects (i.e., projects committed by the agency) are identified beforehand and are excluded from the prioritization process, as they are funded first. Candidate projects identified by the PMP methodology compete for the remaining funds.

5.5.1 Computing the Priority Score

The normalized decision factors (i.e., utility values) are used to compute the priority score for each candidate M&R project. Figure 5.11 illustrates this process. The utility values are shown in the left side of the figure, followed by the hierarchy of decision factors. The numbers in parentheses represent the weights of each decision factor. Note that the weights of the main factors (CC, CTV, IC, LTPB, and LCC) and the sub-factors under CC (CS, RS, CSRD, SKID, STRUCT, VISUAL) and CTV (AADT, TAADT) must sum to 100%. The priority score is computed by multiplying the utility values with their corresponding weights and summing the products as shown in Figure 5.11 for example.

5.5.2 Incremental Benefit-Cost (IBC) Analysis

Once the viable M&R alternatives for each candidate project are identified and their respective priority scores are computed, all combinations of project and M&R alternative are prioritized using the IBC algorithm for any given budget.

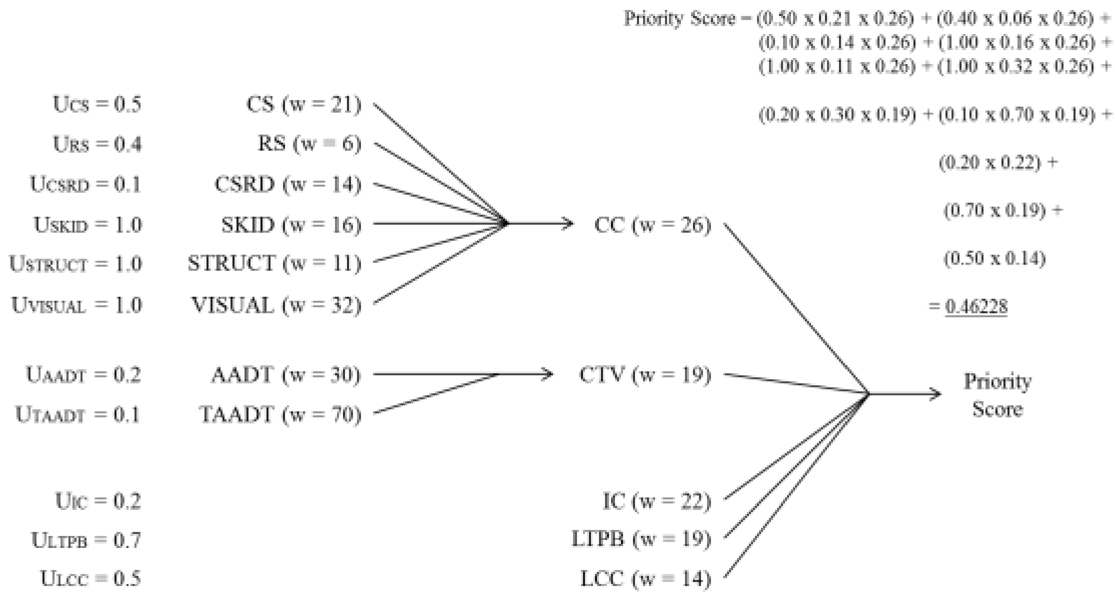


Figure 5.11 Example of Calculating Priority Score

In the case of segments that need treatment, the viable alternatives are sorted in increasing order of priority score (see Figure 5.12). The algorithm first recommends the most cost-effective alternative (i.e., highest priority score per dollar) and if the budget permits, the recommended treatment may be replaced by the next heavier (with higher priority score) alternative. At the network level, candidate projects that yield the greatest IBC ratios are initially prioritized and if there is still available budget, the M&R treatments of the initially prioritized projects may be replaced by heavier (with higher priority score) treatments. This algorithm effectively produces the list of projects that maximizes the total priority score under a given budget (see Figure 5.13).

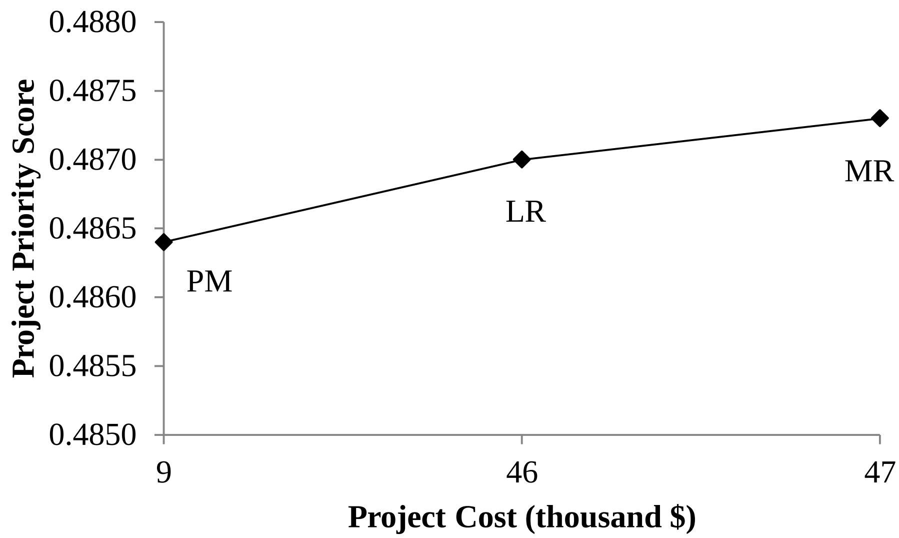


Figure 5.12 Ranking of Viable Alternatives at the Project Level

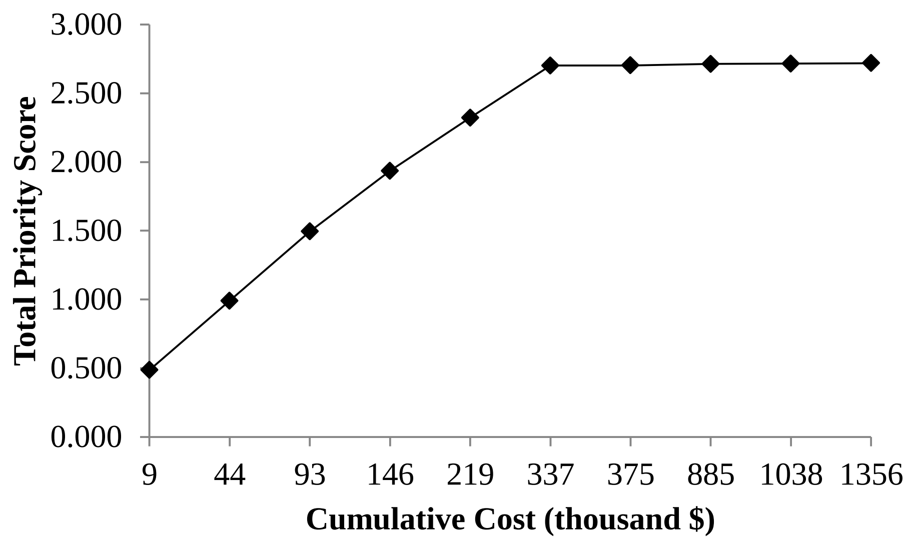


Figure 5.13 Maximization of the Total Priority Score using the IBC Algorithm

Table 5.7 shows an example of project prioritization using the IBC algorithm with six candidate projects. In the first column, the number indicates a unique project while the two-letter code indicates the M&R alternative (e.g., PM for Preventive Maintenance). Note that for instance, Projects 2, 5, and 6 have two viable M&R alternatives each (i.e., PM and MR). These are arranged in a decreasing order of their final IBC ratios.

Table 5.7 Example of Project Selection using IBC

M&R Alterna-tive	Initial Cost, ($K)	Priority Score	Final IBC Ratio	Cum. Cost, ($K)	Selected Projects					
					1	2	3	4	5	6
1-PM	9	0.4864	0.055039	9	PM					
2-PM	35	0.5037	0.014249	44	PM	PM				
3-PM	49	0.5039	0.010368	93	PM	PM	PM			
4-PM	53	0.4420	0.008335	146	PM	PM	PM	PM		
5-PM	74	0.3864	0.005247	219	PM	PM	PM	PM	PM	
6-PM	118	0.3797	0.003222	337	PM	PM	PM	PM	PM	PM
1-MR	47	0.4873	2.32E-05	375	MR	PM	PM	PM	PM	PM
6-MR	627	0.3901	2.05E-05	885	MR	PM	PM	PM	PM	MR
1-LR	46	0.4870	1.6E-05	*						
2-MR	188	0.5057	1.3E-05	1038	MR	MR	PM	PM	PM	MR
5-MR	392	0.3903	1.22E-05	1356	MR	MR	PM	PM	MR	MR

Table 5.7 shows that for a budget of $219,000, Projects 1-PM, 2-PM, 3-PM, 4-PM, and 5-PM should be funded while Project 6 is left untreated. If the budget is increased to $337,000, all projects can be treated with PM. If the budget is further increased to $375,000, the budget is now large enough to apply MR to Project 1 instead of PM as originally recommended. As the budget increases even more, more projects are

assigned MR. This demonstrates the capability of the IBC algorithm to maximize the priority score of the set of projects selected by allowing the replacement of previously considered low-priority score alternatives with a high-priority score alternative whenever the budget permits (Farid et al. 1994; Shahin et al. 1985).

5.6 Projecting Condition to the Next Year

The IBC algorithm generates the list of projects (along with their treatment type) recommended for the first year of the PMP. With this information, network condition for the following year can be estimated using the DS and CS prediction models discussed earlier. As mentioned in section 3, the CDA segmentation method would project each project's condition using the aggregated condition. In contrast, the PDA segmentation method projects the condition of each data collection section.

For projects that have been selected for treatment, their DS and CS immediately after treatment (DS_0 and CS_0) are first computed. This is done by applying the gains in rating (shown earlier in Table 5.3). Then, Equations 5.5 and 5.6 are used to project the condition for the following year. In this case, age would be equal to one since the condition one year after treatment is being computed. The coefficients ρ and β would now be based on the actual M&R treatment applied (see Figure 5.14a).

For segments that have not been selected for treatment, their DS and CS in the following year is projected by using Equations 5.5 and 5.6, respectively. DS_0 and CS_0 would be their current DS and CS, Age would be the computed theoretical age (using the DS-based theoretical age in Equation 5.5 and the CS-based theoretical age in Equation

5.6), and ρ and β would be those from the HR model under the assumption that the last treatment received by the management section is HR (see Figure 5.14b).

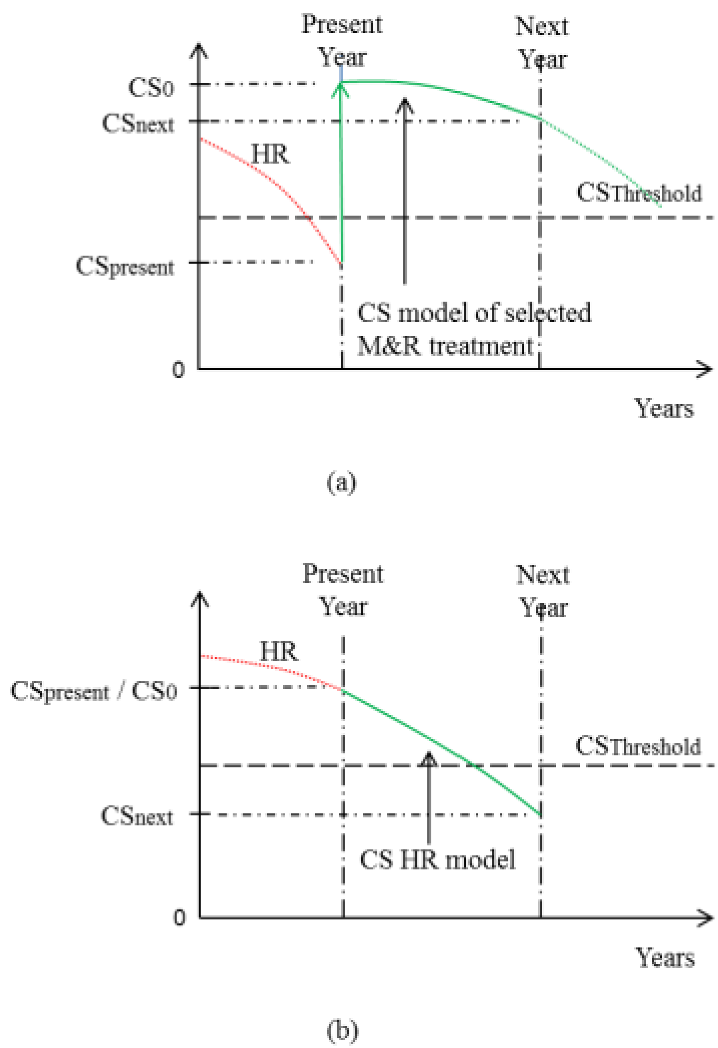


Figure 5.14 Projecting CS to the Next Year

The ride score is computed as a function of the projected CS and DS using Equation 5.3 (discussed earlier). The other condition indicators (CSDR, SKID, STRUCT, and VISUAL) are only used to prioritize projects for the current year as their values (i.e., adequacy/inadequacy of actual assessments) cannot be projected into the future. Thus, their values for the following years are set to NULL.

Once, the projected pavement condition (i.e., CS, DS, and RS) has been computed, the long-term performance benefit, life-cycle cost, and IBC computations are repeated for the next year. This loop continues until the end of the PMP planning horizon (i.e., four years) to generate the yearly list of projects that constitute the four-year pavement management plan.

6. VALIDATION OF THE PROPOSED PMP METHODOLOGY

In this section, the pavement management plans generated by the proposed methodology are compared with the actual available PMP produced by Bryan District. The actual PMP is first introduced followed by analyses of the agreement between the two PMPs in terms of their needs estimates, project boundaries, and effectiveness in attaining network goals. The policy implications of the calculated priority weights are also discussed.

6.1 Available Bryan District PMP

The Bryan district road network consists of 7,075 lane-miles of pavement. Available Bryan district four-year PMP (2012-2015) was obtained from TxDOT and its contents are summarized in Table 6.1.

Table 6.1 Summary of Available Bryan District PMP

Year	Number of M&R Projects	Lane-Miles	Cost
2012	51	486	$12,500,000
2013	72	882	$27,500,000
2014	81	839	$26,000,000
2015	61	791	$22,500,000
		4-Year Average	≈$22,000,000

The total cost of projects planned for 2012 is noticeably low compared to the succeeding years. It is therefore reasonable to assume that the obtained 2012 PMP is incomplete. This is a limitation in using this actual PMP. Thus, corrective measures were undertaken in the analyses to account for this limitation.

6.2 Agreement in Needs Estimates

The uniform annual needs estimate is the average yearly budget (over four years) necessary to eliminate network backlog within four years. Figure 6.1 shows the uniform annual needs estimate for three different cases as compared with the actual budget used in the District's available PMP:

- M&R applied to data collection sections
- M&R applied to segments formed using the CDA method
- M&R applied to segments formed using the PDA method

The first case represents the needs estimate when individual data collection sections are considered independent M&R projects and are prioritized accordingly. While the M&R projects in this case are unrealistic, it provides the "theoretical" needs estimate since a section receives exactly the treatment that it requires regardless of the conditions of its neighboring sections. When projects are formed using the CDA method with 50% reliability (i.e., segment condition is computed as the arithmetic weighted average condition of the data collection sections), the needs estimate is lower than the theoretical estimate. This can be attributed to the masking effect of this segmentation scheme (i.e., local areas with poor condition are masked by the averaging process).Thus, the CDA project formation scheme (with aggregated condition computed at 50% reliability) will result in underestimating the true needs of the network. However, when aggregated condition is computed at 80% reliability, the CDA method tends to produce more realistic results. At this reliability level, the masking of localized deficiencies is minimized while keeping the needs estimate from bloating. Therefore, in the subsequent analyses, an 80% reliability is used when running the CDA.

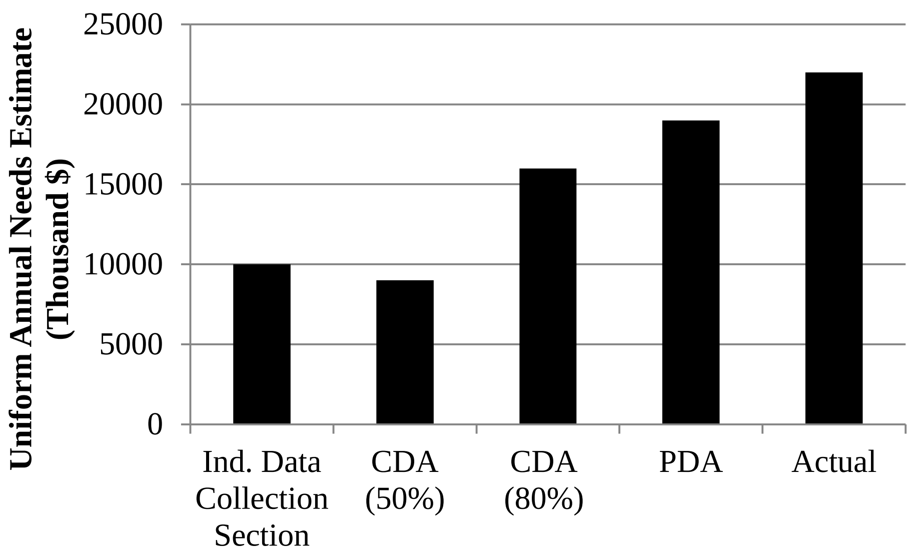


Figure 6.1 Effect of Project Formation Scheme on the Four-Year Needs Estimate (Cost estimated from the actual PMP is not necessarily a needs estimate; it is provided for comparison purposes.)

The needs estimate increases if the PDA approach is used to form projects, compared to estimates obtained from projects formed using the CDA approach and estimates obtained from individual PMIS sections. While localized poor areas are obscured in the CDA, the PDA forms projects around them by grouping them with adjacent sections. This explains the increase in the needs estimate shown in Figure 6.1.

Furthermore, the needs estimate determined using the PDA approach is closer to the actual budget used; suggesting that the PDA produces more realistic results than the CDA.

6.3 Agreement in Project Boundaries

The level of agreement between projects selected by the proposed methodology and those listed in the District's PMP was quantified by the percentage of True Positives (TP) and False Negatives (FN), as follows:

- True Positive: M&R project is selected by the proposed methodology and exists in the District's PMP
- False Negative: M&R project is not selected by the proposed methodology, but it exists in the District's PMP.

Thus, the higher the TP and the lower the FN the higher the agreement between the two PMPs. As a caveat, the word *true* in *True* Positive does not imply that the actual PMP's selection is the *right* project choice in the same way that a *False* Negative does not imply that the methodology *wrongly* identifies a project as needing nothing. These terminologies were only adopted to assess the matching between the proposed PMP and the actual PMP.

Only projects planned for 2012 were evaluated to eliminate the compounding of initial mismatches in later years. Moreover, only the TPs and FNs were compared since the budgets used in developing the PMPs are dissimilar. By using unlimited budget in the proposed methodology, every pavement section recommended for M&R in the actual

PMP should, ideally, also appear in the methodology's PMP; but not every section in the methodology's PMP should be found on the actual PMP. Hence, evaluating the False Positives (FP) and True Negatives (TN) would be inappropriate. Table 6.2 shows the results.

Table 6.2 Agreement Between the Actual PMP and PMP Generated by using the Proposed Methodology(1)

Project Formation Scheme	TP	FN
CDA (at 50% Reliability)	41%	59%
CDA (at 80% Reliability)	55%	45%
PDA	62%	38%

[1]TP and FN are computed based on 486 lane-miles of actual projects

To examine the cause of discrepancies between the PMPs generated by the proposed methodology and the PMP generated by the District, the 51 M&R projects in the District's 2012-2015 PMP were analyzed in detail. The boundaries of each project were compared with the boundaries of the closest CDA- and PDA-formed projects. The methodology was run using unlimited budget to eliminate the potential for leaving out some projects due to limited funding. Analysis reveals four ways by which CDA- and PDA-formed project boundaries may agree/disagree with actual project boundaries. These four cases are illustrated in Figure 6.2, where False Positives (FPs) represent pavement sections adjacent to actually planned sections and yet were not included in the project but were selected by the proposed methodology; TPs and FNs are as defined earlier.

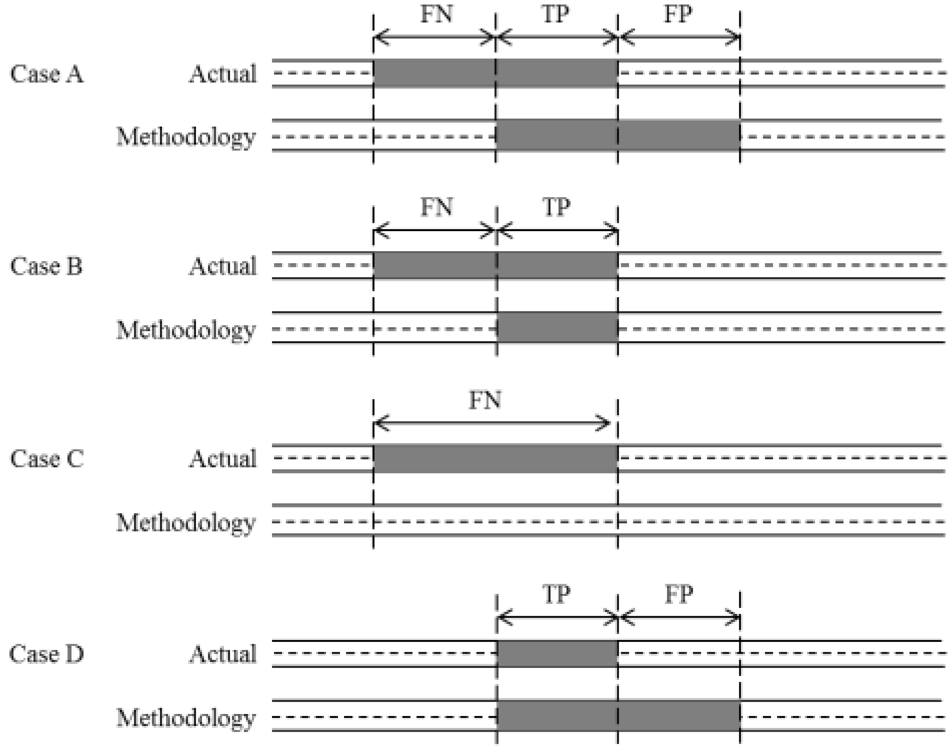


Figure 6.2 Four Cases of Match/Mismatch Between Actual and the Methodology's Project Boundaries

Table 6.3 shows the average CS of the sections that fall under each mismatching case of Figure 6.2. The results are explained as follows:

- For case A, the average CS of FPs for both CDA and PDA (79 and 75) are lower than those of the FNs (92 and 95). Thus, including them in the project is more logical than choosing the relatively good sections;
- For case B, the average CS of FNs for both CDA and PDA (94 and 96) indicate very good condition. Thus, the methodology's decision not to select them for M&R is justified;

- For case C, the average CS of FNs are likewise indicative of very good condition. Thus, not selecting them for M&R is again justified;
- For case D, the average CS of FPs are close to that of the TPs thus, they should have been recommended for M&R as well.

The above discussion shows that while there are indeed mismatches in project boundaries, the methodology's project limits are more justifiable based on pavement condition.

Table 6.3 Average CS for each Type of Match/Mismatch

Case	CDA (80% Reliability)			PDA		
	TP	FN	FP	TP	FN	FP
A	74	92	79	78	95	75
B	81	94	NA	79	96	NA
C	NA	97	NA	NA	99	NA
D	69	NA	67	68	NA	71
All Cases	72	95	71	74	96	72

6.4 Pavement Network Condition under the Methodology-Generated PMP and Actual PMP

In this analysis, the impact on network condition of implementing the actual PMP is compared with that of the methodology's PMP. The actual budgets shown in Table 6.1 were used in running the methodology to facilitate proper comparison. Figures 6.3 to 6.5 show the average and minimum network CS brought about by the PMPs.

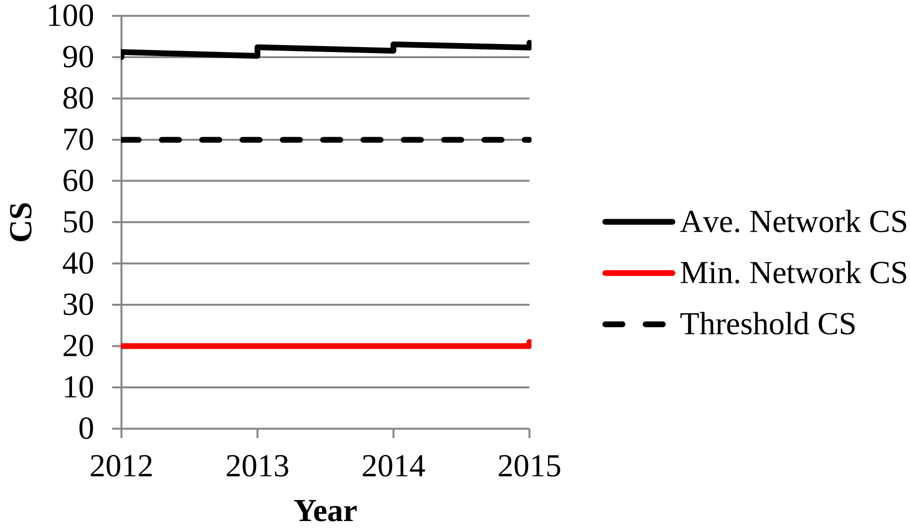


Figure 6.3 Average and Minimum Network CS Predicted for the Actual PMP

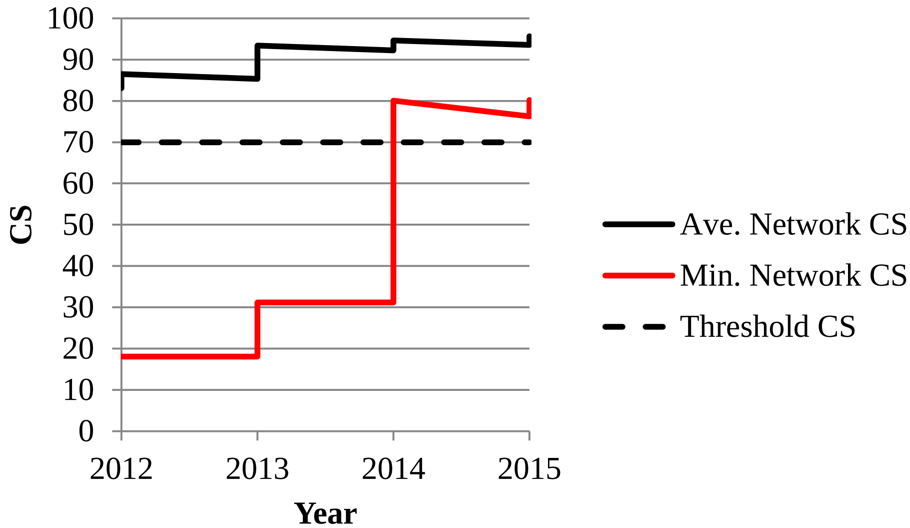


Figure 6.4 Average and Minimum Network CS Predicted for the PMP Generated by the Proposed Methodology (CDA Project Formation Scheme with 80% Reliability)

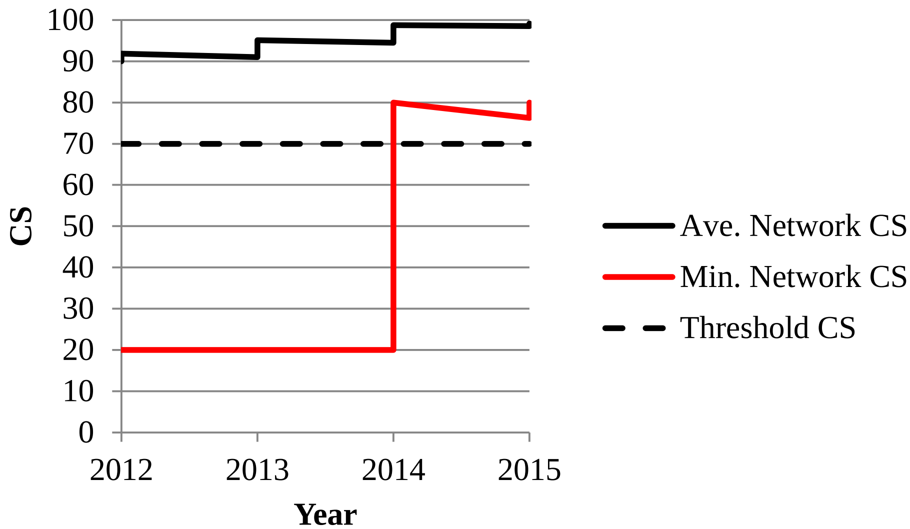


Figure 6.5 Average and Minimum Network CS Predicted for the PMP Generated by the Proposed Methodology (PDA Project Formation Scheme)

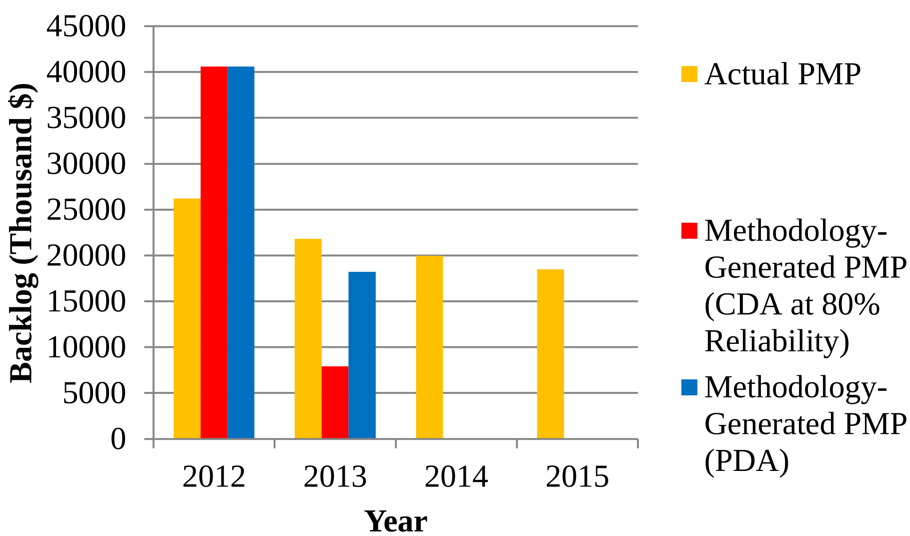


Figure 6.6 Backlog Produced by the Actual and the Methodology's PMPs

The average network conditions produced by the three PMPs are generally comparable. In terms of the minimum network CS though, the PMPs generated by the methodology perform better. This is also shown in Figure 6.6 where the actual PMP maintains a backlog of untreated projects while the proposed methodology managed to eliminate the backlog by 2014. Likewise, the methodology's PMPs are more effective in attaining the goal of having 90% of network lane-miles in "Good" or better condition as shown in Figures 6.7 to 6.9. The methodology's PMPs are predicted to exceed this goal by 2013 while the actual PMP barely meets this target. This indicates that, for the same given budget, the methodology is allocating funds to projects that have greater impact on improving network condition.

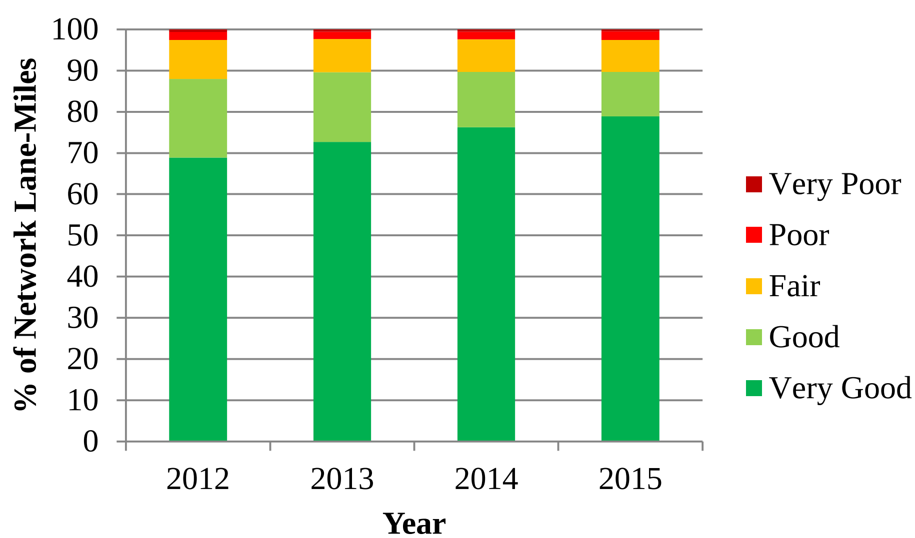


Figure 6.7 Network Condition Predicted for the Actual PMP

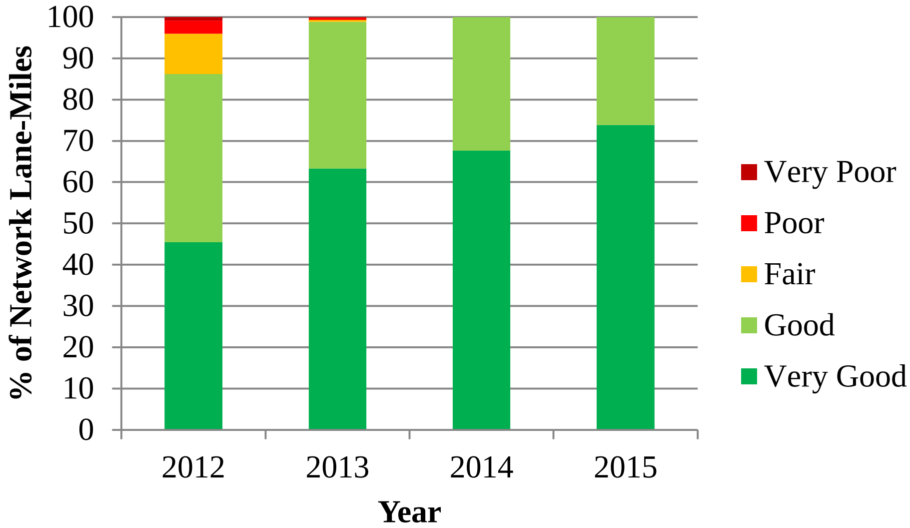


Figure 6.8 Network Condition Predicted for the PMP Generated by the Proposed Methodology (CDA Project Formation Scheme with 80% Reliability)

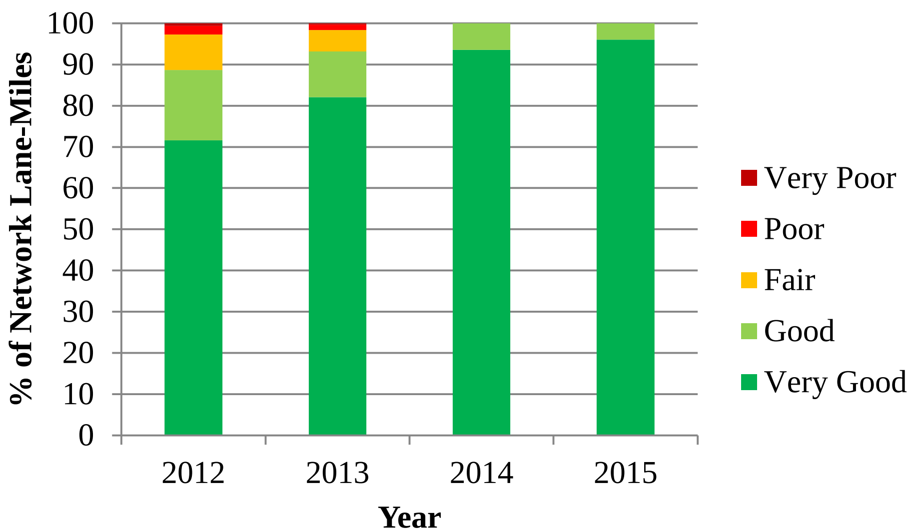


Figure 6.9 Network Condition Predicted for the PMP Generated by the Proposed Methodology (PDA Project Formation Scheme)

The above analyses validate the soundness and justifiability of the developed methodology. While mismatches exist between the district's and the methodology's PMPs, the methodology's manner of allocating resources was proven to be more justifiable and effective in attaining network goals.

These results suggest that while the decision makers have their priorities in mind, the subjectivity and ad hoc nature of the PMP production process may actually lead them away from their intended outcomes. Thus, this research offers a tool that will perform the analysis systematically and justifiably so that optimum results that are consistent with the districts' priorities are attained.

6.5 Policy Implications of the Priority Weights

The policy implications of the proposed methodology along with the weights assigned to the prioritization decision factors are investigated in this section. As discussed earlier, the factors used in prioritizing M&R projects were classified into short-term (i.e., pavement current condition, current traffic volume, and initial cost) and long-term factors (i.e., long-term performance benefits and life-cycle cost). The weights of these factors were obtained through a state-wide survey to deduce the districts' priorities when developing their annual PMPs. The question is what prioritization policy would the proposed methodology encourage when these weights are used: a worst-first policy or balanced policy?

Figures 6.10 and 6.11 compare the ranking of M&R projects according to the proposed methodology (along with the state-wide decision factors' weights) to the ranking of these projects according to the worst-first approach. Each point in Figures 6.10 and 6.11 represents a candidate project formed using the CDA and PDA respectively. A project's ranking in the priority list when all main criteria (i.e., balanced approach) are considered is given by its position along the horizontal axis. On the other hand, its ranking when a purely worst-first approach is used is given by its position along the vertical axis. A worst-first approach is defined here as ranking of M&R projects in an increasing order of their condition score. Thus, a point near the left side of the graph is a project that has high priority as determined by the IBC analysis while a point near the horizontal axis is a project that has high priority in terms of its condition score (i.e., a project with low CS value).

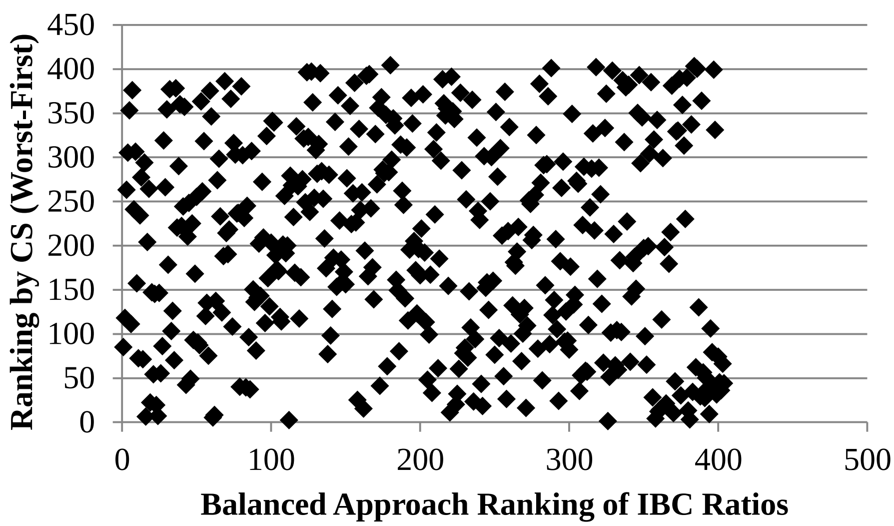


Figure 6.10 Comparing Ranking of Projects in a Balanced Approach and a Worst-First Approach using CDA as Project Formation Scheme

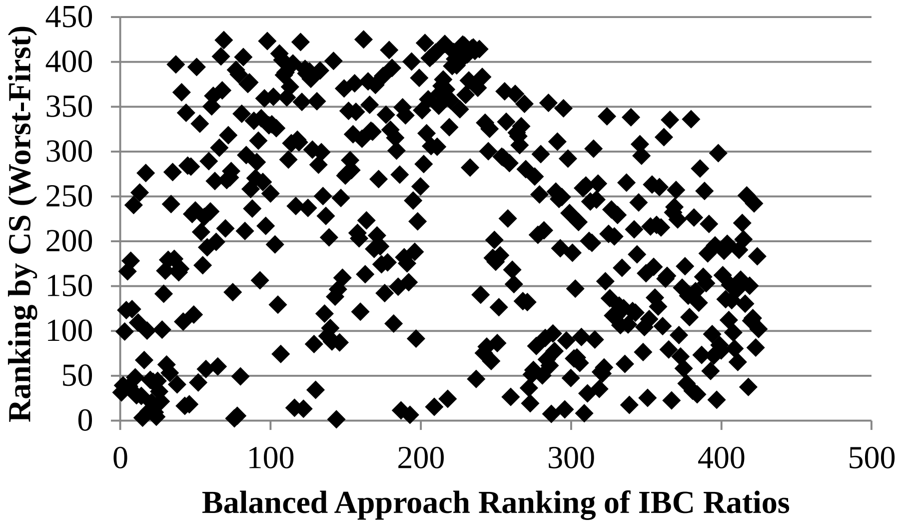


Figure 6.11 Comparing Ranking of Projects in a Balanced Approach and a Worst-First Approach using PDA as Project Formation Scheme

Since the points in both Figures 6.10 and 6.11 are well-scattered across the plot, this suggests that the weights obtained from the survey of TxDOT's districts when used in the proposed PMP methodology cause a ranking of projects that is sufficiently different from that of a worst-first approach. Notwithstanding the relatively low weights assigned to the long-term factors, these weights appear to be significant enough to make the long-term factors affect the rankings, and consequently, project selection. Had the points appear to congregate diagonally from the origin, (i.e., along the equality line) then that will imply that the weights obtained from the survey are indicative of a worst-first strategy.

Furthermore, consider Figures 6.12 and 6.13. This time, the ranking from a balanced approach is compared with that of a long-term approach. A long-term approach is represented by setting the weights of the short-term factors to zero while normalizing the weights of long-term performance benefit and life-cycle cost (i.e., eliminating the effect of the short-term factors on the project selection). Figures 6.12 and 6.13 illustrate that the rankings produced by the balanced approach have close resemblance to that produced by a long-term approach despite, again, of the relative low weights assigned to the long-term factors. This analysis shows that the weights obtained from TxDOT districts when used in the proposed methodology reflect a departure from a worst-first approach in prioritizing pavement M&R.

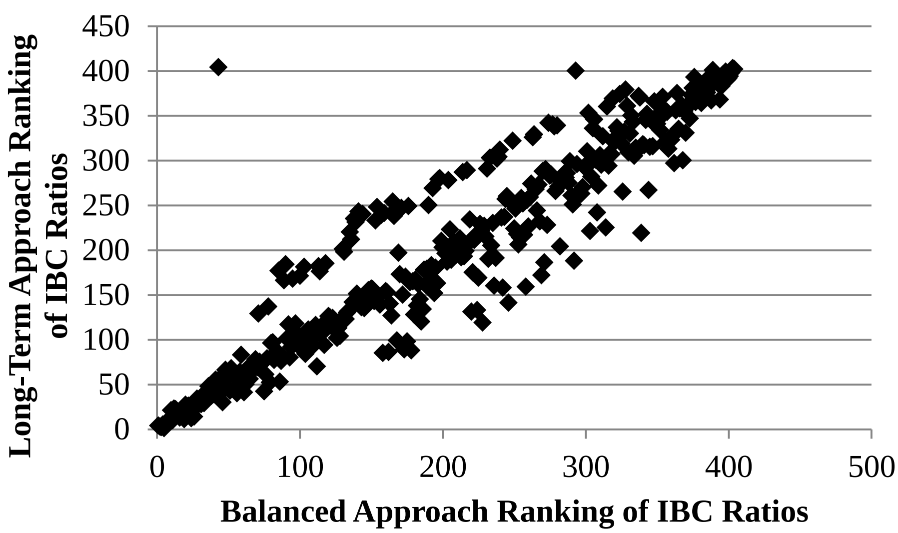


Figure 6.12 Comparing Ranking of Projects in a Balanced Approach and a Long-Term Approach using CDA as Project Formation Scheme

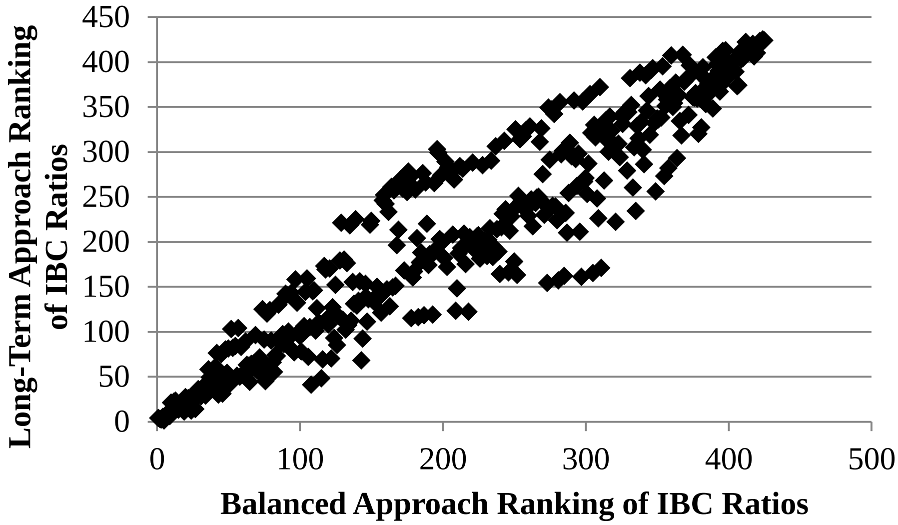


Figure 6.13 Comparing Ranking of Projects in a Balanced Approach and a Long-Term Approach using PDA as Project Formation Scheme

7. SUMMARY AND CONCLUSION

A methodology for forming and prioritizing pavement M&R projects was developed for use in creating multi-year pavement management plans. This provides a systematic and justifiable manner of prioritizing projects while considering the decision makers' priorities. The methodology was developed using data from the Texas Department of Transportation Pavement Management Information System database and was designed for use by its district engineers.

Key decision factors were considered that reflect both short-term and long-term criteria in prioritizing M&R projects. A survey of district decision makers was carried out to obtain the priority weights of the decision factors using the Analytic Hierarchy Process. To produce realistic results, the methodology was designed to form and prioritize realistic M&R projects. Two algorithms were used to form projects out of contiguous data collection sections: the Cumulative Difference Algorithm and the Proximity to Deficient Areas approach. A priority score was computed for each candidate project based on the key decision factors considered and their weights. The Incremental Benefit-Cost technique was adopted to generate the set of projects that maximizes network's priority score under budgetary constraints. Finally, future network condition was projected using performance prediction models and the process is repeated throughout the planning horizon to produce a multi-year pavement management plan.

The methodology was tested using data from TxDOT's Bryan district to validate the results. The following conclusions can be made based on this research.

- The developed methodology combined with the decision factors' weights reflects a departure from a worst-first approach to a long-term approach in prioritizing M&R projects.
- The CDA project formation scheme is prone to obscuring localized deficient sections that may lead to grossly underestimating network needs. This can be corrected by increasing the reliability level when computing a project's aggregated condition. An 80% reliability is recommended.
- Mismatches exist between TxDOT's PMP and that produced by the methodology. However, the methodology's selections were shown to be more justifiable as it selects pavements that are in greater need of M&R.
- Given the same budget, the methodology's PMP yields better network condition than TxDOT's PMP.

In conclusion, these results highlight the potential of the developed methodology to improve pavement management planning by incorporating district priorities and producing sound and justifiable pavement management plans that result in optimum network performance.

8. RECOMMENDATIONS AND FUTURE WORK

This research provides the basic framework for a pavement M&R project formation and prioritization methodology that incorporates decision makers' priorities. Throughout the process, a number of features may be improved. The following are recommendations for both potential users (i.e., district engineers) and future researchers.

- Agencies are encouraged to develop and use common location referencing system for all databases to facilitate easy searching and matching of pavement information.
- Future work can focus on identifying potential errors in pavement data and replacing them with reasonable and realistic values.
- Other potential non-technical decision factors may be explored for consideration in the PMP methodology. Examples include accident rate, aesthetics, public complaints, and the needs of adjacent jurisdictions; however, the decision problem must remain at a manageable size.
- TxDOT may consider expanding the survey to obtain a larger sample size or alternatively, hosting a brainstorming session for decision makers to discuss the factors, the hierarchy, and the weights to be assigned to them.
- The CDA may be further improved by comparing the trigger criteria not with the group's average condition but with the individual data collection section's condition. Such modification practically combines the benefits of the CDA and PDA approach.

- The trigger value used in the methodology is based on CS which is a composite index. Future work may consider using individual distresses as trigger criteria for a more detailed assessment. This will entail pavement condition to be projected using individual distresses instead of DS and CS as done in this research. While this will inevitably increase the size and complexity of the algorithms, it is nevertheless worth considering.
- The use of “hybrid” projects reveals the need for a more accurate manner of estimating project cost. For instance, project cost may be different even for projects of the same length and treatment type depending on the uniformity of their condition and other roadway features.
- Utility curves could be developed to convert project attributes to utility values, instead of normalizing linearly as performed in this research. This, however, requires commitment on the part of the decision makers to develop such curves.

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