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Use of Comparative Efficiency Analysis to Optimize Transportation Infrastructure Maintenance Investment Strategy

By

Teresa M. Adams, Professor
University of Wisconsin-Madison
adams@engr.wisc.edu

Emil Juni, Graduate Research Assistant
University of Wisconsin-Madison
erjuni@wisc.edu

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DISCLAIMER

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1. Background

The National Cooperative Highway Research Program (NCHRP) has published reports promoting performance-based analysis as a way to improve the effectiveness and efficiency of maintenance quality assurance programs. This suggestion directly affects the way maintenance procedures for transportation infrastructure are conducted. NCHRP Report 666 describes methods that can be used by state transportation agencies to set performance targets to achieve multiple objectives, and ways to improve data management systems within the agencies to support performance-based decision-making.

NCHRP Report 666 defines performance-based decision-making as a way of using performance measurement to guide resource allocation decisions in managing transportation asset management as well as in operations, investment, planning, and policy development. This method is increasingly used by DOTs and other transportation agencies. NCHRP Report 666 focuses on specific methods for setting performance targets, which is one of the core ideas of performance-based decision-making (*1*).

There is clearly an emerging need for a way to optimize and improve the budget allocation process for transportation infrastructure maintenance in order to avoid spending unnecessary amounts of money on projects with little significance. In other words, more than ever, it is necessary to be certain that available money is spent where it counts the most. To fulfill this need, we must figure out the best way to analyze the performance efficiency of transportation maintenance to ensure productive spending and find the best way to spend the limited amount of funds available while being certain that the money is spent in the most efficient fashion.

2. Performance-based maintenance in state transportation agencies

Performance-based maintenance in transportation is a way to preserve transportation infrastructure effectively by defining target conditions of infrastructure assets that have to be met and by focusing maintenance efforts of these assets on meeting these predetermined targets. The growing need for efficient maintenance spending had the natural effect of increasing focus on performance management in maintenance of transportation assets. This has driven interest in performance-based maintenance in transportation agencies in most states in the United States. In the past decade, this growing use of focus in performance management is also influenced by the increasingly popular concept of maintenance quality assurance. According to NCHRP Synthesis 426, performance-based analysis gives more explicit recognition and emphasis to performance accountability reporting, operations-related features and activities, and more comprehensive accounting of highway performance and cost (*2*).

Currently, many states in the United States are implementing performance-based maintenance management centered on Level of Service (LOS) of transportation assets. Each asset type is assigned performance measures that reflect their degree of usability, which shows how good conditions are from the point of view of users. As different states approach transportation asset management differently, the types of performance measures being used often differ slightly between states, but the basis of the asset management programs are the same. There have also been efforts to compile comprehensive resources on specific quantitative measures for maintenance quality in order to inform Maintenance Quality Assurance programs in different states about what measures to use and what other programs are using (*3*). Most if not all of these programs perform their measurements periodically (mostly annual, some biennial) with similar organizational goals, which are to:

- Develop needs-based maintenance estimates and prioritize needs;
- Develop and support budget justification requests;
- Allocate resources among jurisdictional areas within the state (districts/regions);
- Quantify and analyze relationships between cost and condition;
- Support communication with stakeholders;
- Track transportation infrastructure system condition and performance; and
- Prioritize maintenance activities and operations.

From experiences in implementation of performance-based maintenance around the country, it is clear that targets play an essential part of performance-based maintenance and resource analysis. A target is defined as a measureable goal for an individual asset type at the end of a maintenance cycle. Setting targets includes balancing among competing objectives and perspectives of multiple stakeholder groups, while considering the amount of resources available. As such, targets become part of the business process that directly links organizational goals and objectives to available resources and results. The emphasis on targets in performance-based resource analysis is a key component in evaluating the effectiveness of investment decisions.

Setting targets usually involves reconciling strategic requirements with the reality of available resources and capabilities. This process must be understood and coordinated at many levels, all of which can influence the outcome. In general, the process of setting targets in transportation agencies starts with conducting a self-assessment to ensure that the targets are defined in a manner that reflects the reality of the agency. After that, the agency needs to define the values of the targets to align with various measures and priorities of the stakeholders, place them within the context of the overall agency strategy, select the framework, define strategies and actions, and finally apply budget constraints. It is also important to understand the different types of targets. Some agencies may define targets as desirable, but not attainable, or simply base them on historic trends (*4*).

Figure 1 shows the Performance Management Framework as described in NCHRP Report 666. Target setting is displayed at the center of the process, immediately after the goals and objectives are set, and acts as a guiding point for resource allocation. As discussed in the previous section, some state transportation agencies have already implemented a version of this procedure. The challenges in implementing a performance-based approach include figuring out how to determine targets, incorporating these targets into long-term maintenance planning, and using them to track progress, as well as a point of comparison for measuring the results in each maintenance cycle.

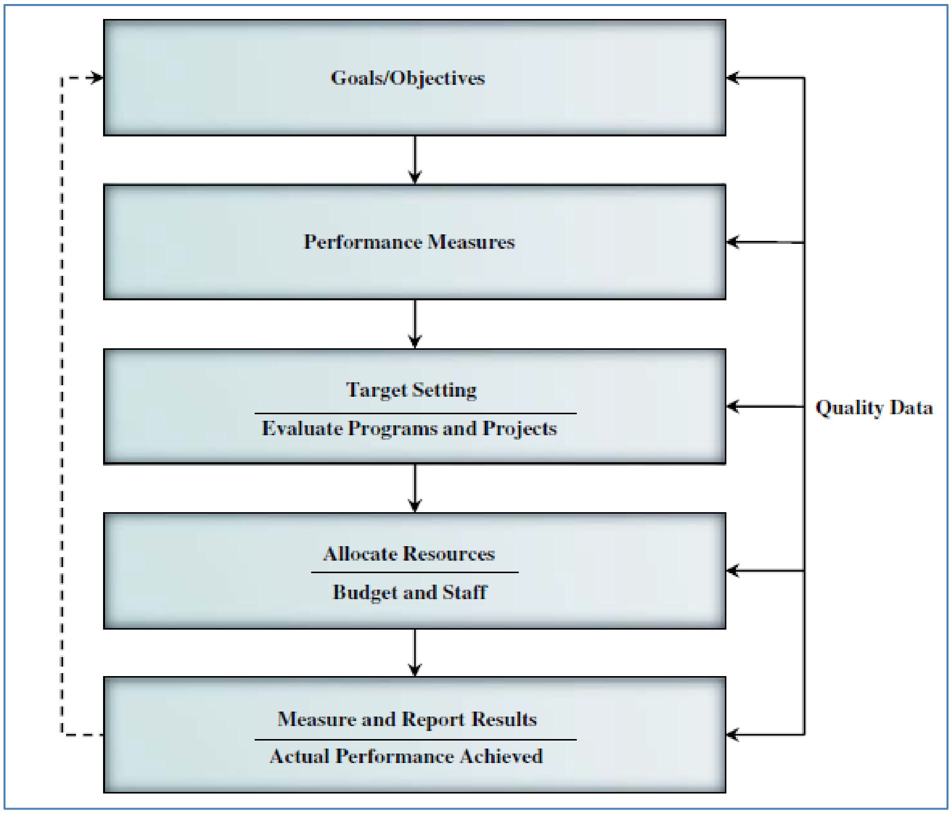

Figure 1 Performance Management Framework (*1*)

For each type of transportation asset, targets are set as a goal state at the end of each maintenance cycle. In some cases these target values are planned and set for years in the future, while in other cases they are adjusted according to the availability of allocated funds each year or according to other factors. This approach greatly helps the agencies to manage the continuous and ever-evolving maintenance process. By basing resource allocation and maintenance efforts on achieving target values, the analysis of the maintenance process can shift toward focusing on the performance of maintenance. The efficiency of resource allocation can be determined by comparing the results to the target values.

The presence of targets facilitates a dynamic way to assess maintenance performance, and encourages efficiency of effort. The performance of a maintenance process is then judged by comparing the measured condition at the end of a maintenance process with the target value. Maintenance is considered to perform well when the measured condition hits or comes close to the target. This view of focusing maintenance efforts on target values is consistent with the current federal policy of efficient spending (*5*) and makes it easier to find ways to improve and manage spending efficiencies while the availability of resources increases and declines throughout the years.

The performance management framework shown in Figure 1 can be viewed as periodical cycle. Commonly, there is a continuous cycle of expenditures, maintenance work, and condition assessment; a process that in this study we are calling the 'cost-condition cycle'. The cost-condition cycle begins with the availability of funds for transportation maintenance, which based on current infrastructure conditions are allocated and distributed to perform maintenance. The results of these maintenance actions are shown as measured conditions or the levels of service of the many parts of the transportation system at the end of the periodic maintenance cycle. These conditions will have an effect on the decision-making process for distributing the available funds in the following year, when the cycle starts again. To simplify, there are three distinct stages in the continuous cycle of infrastructure maintenance: allocation of funds; selection and performance of maintenance actions; and assessment of conditions.

Figure 2 illustrates the cost-condition cycle and shows how the three stages of cost-condition cycle interact with each other. This diagram also identifies a list of parameters as an example of factors that affect each stage of the process. In each stage, two different types of parameters are shown. Controlled parameters can be changed and/or planned for by maintenance administrators, while uncontrolled parameters are external conditions that cannot be controlled by the maintenance administrators, but that affect the process.

In the first stage of the cost-condition cycle, infrastructure asset conditions are considered and maintenance policies are discussed and reviewed, targets are set, and funds are distributed. The second stage of the cycle consists of the actual maintenance work. There are routine maintenance tasks to perform and some reactive maintenance that may need to be carried out. All of these maintenance tasks are performed according to the priorities established in the first stage. In stage three, at the end of a periodic maintenance cycle, condition assessment of the system is performed. The results from this assessment show the current status of the overall transportation infrastructure network. These results directly influence policies and fund distribution for the subsequent period, where the process repeats starting with the first stage. In each period these stages affect one another in a continuous fashion, forming a cycle of maintenance.

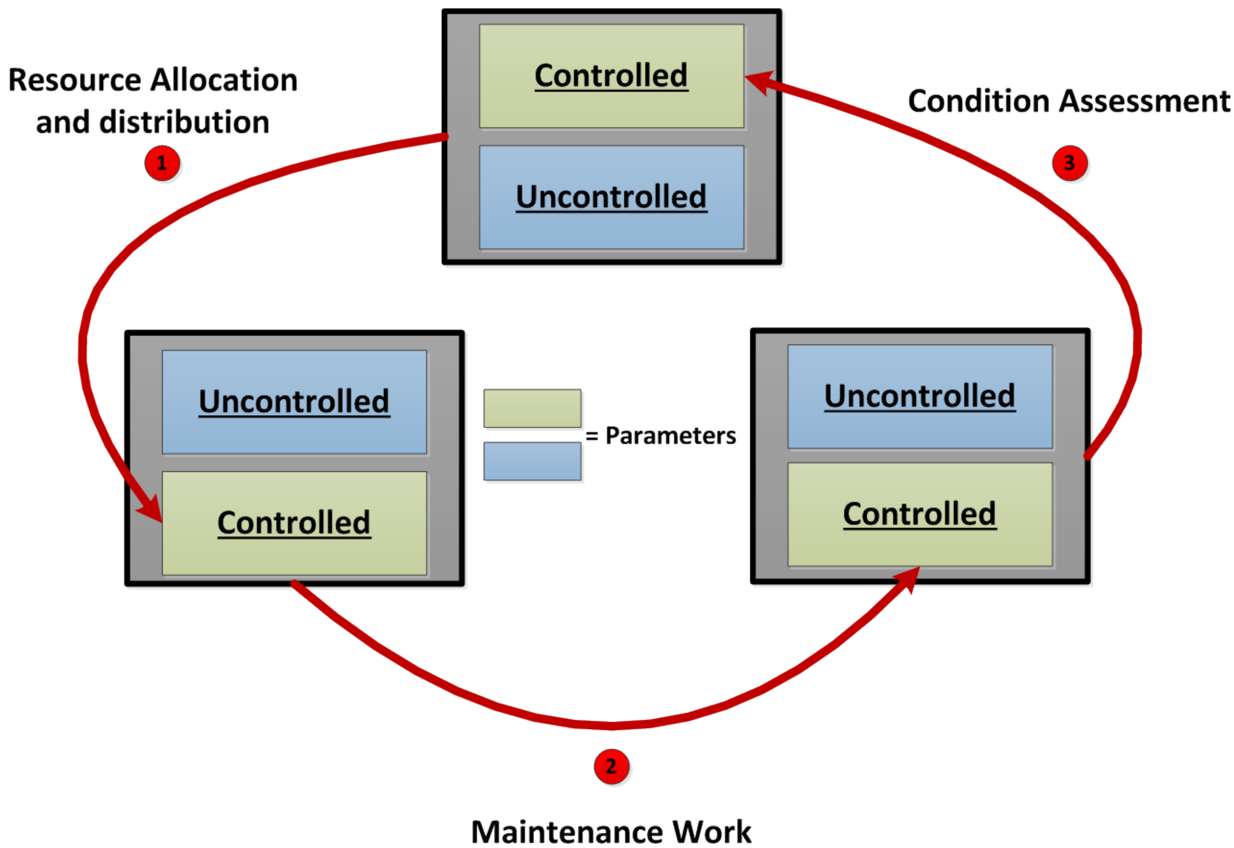

Figure 2 Diagram of Cost-Condition Cycle

Figure 2 shows that the parameters drive each stage in the cost-condition cycle and determine how the cycle progresses. If we consider one cycle as a single period of the maintenance process, we can then examine all the parameters in the cycle from any of the stages. Depending on what they are, these parameters can be regarded as input or output parameters of that cycle. For example, parameters between stages one and two might be Vehicle Miles Traveled (VMT) on highways or bridges, any kind of weather patterns that might affect road or bridge conditions, or the action of maintenance works themselves. Between stages two and three, the conditions and Level of Service (LOS) of the assets, certain local maintenance policies, or other special circumstances are some of the parameters that could be used. Budget availability, statewide maintenance policies, regional target settings, and similar factors form the important parameters between stage three and stage one of the subsequent maintenance cycle.

These parameters are then categorized whether they are considered input or output parameters. One of the most important input parameters is expenditures, or the amount of money spent for that maintenance cycle. Other parameters such as VMT, bridge deck area, and weather patterns are also considered input parameters. Condition ratings, on the other hand, are based on the condition assessment performed at stage three of maintenance cycle, and are considered as output parameters.

Following the basic economics concept of production function, which defines the capability of an entity to produce an output based on the quantity of its inputs, the research can now focus on the multiple input parameters in the maintenance process and the effect that they have in producing a given condition. Based on what was explained in the previous section about spending efficiency, 'maintenance efficiency' acts as a representation of technical efficiency of the maintenance process. In general, technical efficiency is defined as the effectiveness of a set of inputs in producing outputs. It is also sometimes viewed as the ability of a system to avoid waste by producing as much output as input usage allows, or by using as little input as output production allows (*6*).

3. Maintenance efficiency and parameters

The maintenance process is a system with multiple input parameters and condition ratings as output parameters. Maintenance administrators want to make sure that the maintenance process is as efficient as possible. To review the efficiency of this maintenance process, the input and output parameters of a maintenance cycle are observed. A maintenance cycle is regarded as efficient when condition assessments show the best possible outputs possible after considering the effects from the amount of money being spent for that cycle and other input parameters involved in the cycle. Maintenance efficiency is highly dependent on these parameters. Different parameters have different effects on the outcome of a maintenance cycle, and thus have a great impact on its efficiency. This study will show an example of a way to identify characteristics of these parameters, and use this knowledge to improve efficiencies of maintenance systems. To do this, the parameters that significantly affect the efficiency of the maintenance cycle for each particular asset type were observed. Internal and external factors that highly affect the maintenance process during a maintenance cycle are called 'significant parameters' and are essential for the analysis.

Infrastructure assets have different characteristics. Significant parameters of a maintenance process vary depending on the type of infrastructure assets being investigated. While similar types of assets may share some parameters, generally parameters affecting the maintenance process of one type of asset are not the same as the ones affecting a different type of asset. For example, total bridge deck area is important in investigating bridges, while total lane miles is important in investigating the maintenance efficiency of pavement. Furthermore, these parameters need to be quantifiable, either as a raw measure directly taken from condition assessment, or an index value calculated from multiple data items.

For the case studies in this report, we decided to observe the maintenance efficiency of bridges, so the above rules in selecting parameters were applied to identify the significant parameters for bridge maintenance. The amount of money spent on bridge maintenance is the most important input parameter in the analysis. Maintenance expenditures for bridges are usually recorded at the activity level (e.g. crack seal, expansion joints) and summarized at jurisdictional levels (county, district, or region) as needed. This study uses region level expenditure data for bridge maintenance from 2009 to 2013 in Wisconsin.

The other important parameter in bridge maintenance is the sufficiency rating (SR). A bridge's sufficiency rating is determined during periodical bridge inspection and is intended to indicate a measure of the ability of a bridge to remain in service. The SR is a composite rating that is calculated using a formula that includes various factors determined during bridge field inspection and evaluation. Because SR represents the condition of the bridge, we consider the

SR an output parameter. Since it is mandatory for states to annually report bridge conditions, SR for bridges are available and can be retrieved from the National Bridge Inventory (NBI) published by Federal Highway Administration (FHWA).

Other significant parameters for bridges that we are also including are the total bridge area, total deficient bridge area, and average daily traffic (ADT). Total bridge area is the amount of total area of bridge deck in service. Total deficient area is defined as an aggregated area of the bridge that has structural deficiency (which could be caused by having major deterioration that reduces the bridge's ability to support vehicles) and functionally obsolete area (caused by not being up to current standards (e.g., bridges that do not have adequate lane widths, shoulder widths, or vertical clearances to serve current traffic demand). ADT measures the volume of vehicle traffic passing over the bridge, showing how much a bridge is actually being used daily.

Finally, one last factor to be included is the effect of inclement weather on the condition of the bridges throughout the period, which is especially important to consider in locations with harsh winter weather. Studies have shown that temperature significantly affects deterioration rates of bridge elements (*7*). For this study, we use the Winter Severity Index (WSI), which is a composite index of multiple weather parameters that is used in Wisconsin to represent the harshness of the winter months or the entire season with a single number. Table 1 shows these significant parameters for bridges, their types, and whether they are considered as input or output parameters in the modeling process.

Table 1 List of Significant Parameters for Bridges

Name	Parameters	Type
EXP	Bridge Maintenance Expenditures	Input
ADT	Average Daily Traffic	Input
Area	Total Bridge Area	Input
WSI	Winter Severity Index	Input
SR	Sufficiency Rating	Output

4. Method

The method being used in this study is based on Data Envelopment Analysis (DEA), a non-parametric method that relies on the concept of comparative efficiency, where multiple systems are compared on their efficiencies in producing results. The general use of this method is to determine, compare, and evaluate performance of multiple production entities by modeling maintenance cycles without explicitly formulating assumptions and variations that are required in other, parametric regression models. DEA modeling is usually implemented by companies that have multiple production entities and want to compare performances of these entities to measure how efficient they are compared to each other. A common example in usage of DEA is when a bank analyzes performances of its multiple branches within one city.

DEA uses a ratio of a total factor productivity to measure performance by attributing a virtual weight to each production entity's input and output. Total factor productivity is an economics concept that explains a variable that accounts for effects in total output that is measured as an effect of technological change. In DEA, entities' efficiency in producing outputs is then calculated using a linear optimization process that tries to maximize each entity's ratio by finding the best set of weights for each entity. The optimization process is constrained by existing available data so that each production entity is compared against the best observed performance. The set of peer production entities compared using DEA modeling are called Decision Making Units (DMUs). A DMU refers to any entity that is to be evaluated in terms of its efficiency, which in this study is defined as a DMU's ability to convert maintenance expenditures and other external factors (inputs) into conditions (outputs) relative to other DMUs in the model.

In 2009, Ozbek, et. al. illustrated the use of DEA in performing comparative performance measurement of maintenance practices between state DOTs. This 2009 study explained how a mathematical method based on production theory and the principles of linear programming like DEA enables us to assess how efficient an organization is in using resources available to it to generate results, relative to other organizations. The study discussed in detail the theory and formulations of DEA models, and also the steps needed to generate DEA models for problems related to transportation infrastructure. According to Ozbek et al., the process of DEA modeling starts by defining and selecting DMUs, followed by defining and selecting input and output variables, and after that the selection of DEA model and formulation (*8*).

In transportation infrastructure research, DEA modeling has been used as a tool in comparative performance analysis, to compare relative efficiency of maintenance process between DMUs in the same level of jurisdictional area (e.g., counties within a region, regions within a state, etc.). Applying the concept of relative efficiency model, a DMU is to be rated as fully efficient if the performances of other DMUs do not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs. This model is also called the Charnes, Cooper, and Rhodes (CCR) Model, and is the original model of DEA introduced in 1978 (*9*).

The CCR model states that in a system where there are *n* DMUs to be evaluated, DMU_j consumes amount x_{ij} of input *i* and produces amount y_{rj} of output *r*. With the assumption that x_{ij} >= 0 and y_{rj} >= 0 and that each DMU has at least one non-negative input and one non-negative output, the CCR model is then constructed as follows:

$$Maximize\ H_0 = \frac{\sum_r^s u_r y_{r0}}{\sum_i^m v_i x_{i0}}$$

$$subject\ to$$

$$\frac{\sum_r^s u_r y_{rj}}{\sum_i^m v_i x_{ij}} \leq 1\ for\ j = 1, \dots, n,$$

$$u_{r,} v_i \geq 0\ for\ all\ i\ and\ r$$

Where:
H_0: efficiency score of a single DMU
u_r, v_i: weights of output r and input i of the *j*-th DMU, all non-negative
y_{rj}, x_{ij}: quantity of output r and input i of the *j*-th DMU, all non-negative
s: number of outputs
m: number of inputs
n: number of DMUs being considered

The formula shows that we are maximizing the efficiency score of DMU *o* (H_o), with *u* and *v* the respective weight vectors of the output and input parameters based on the parameter data. This efficiency score is calculated as the summation of weighted outputs divided by the summation of the weighted inputs. As DEA is a modeling formula based on technical efficiency, this means that in the most efficient system, resources (inputs) are considered to be transformed into goods (outputs) without waste. This explains the first constraint which says that the maximum possible value for the ratio is 1. The second constraint ensures that each DMU in the model has at least one non-negative input and one non-negative output. The formula is then solved *n* times for each DMU to measure all the DMUs' efficiency scores, utilizing a linear programming optimization technique to find the optimal solutions.

Table 2 shows an example of a set of six DMUs with two inputs and one output, where the output value is unitized to 1 (*10*).

Table 2 Input-Output Values of Example Data Set

	DMU	A	B	C	D	E	F
Input	x_1	4	**7**	**8**	4	2	10
	x_2	3	**3**	**1**	2	4	1
Output	y	1	**1**	**1**	1	1	1

Focusing on DMU B: maximize $H_b = 1*u$

Subject to: $7v_1 + 3v_2 = 1$

$u \leq 4v_1 + 3v_2$ (A) $u \leq 7v_1 + 3v_2$ (B) $u \leq 8v_1 + 1v_2$ (C)

$u \leq 4v_1 + 2v_2$ (D) $u \leq 2v_1 + 4v_2$ (E) $u \leq 10v_1 + 1v_2$ (F) $u, v_1, v_2 \geq 0$

Substituting $v_2 = (1 - 7v_1)/3$ in A, B, C, D, E, F:

$u + 3v_1 \leq 1$ (A) $u \leq 1$ (B) $3u - 17v_1 \leq 1$ (D)

$3u + 2v_1 \leq 2$ (D) $3u + 22v_1 \leq 4$ (E) $3u - 23v_1 \leq 1$ (F) $u, v_1, v_2 \geq 0$

Figure 3 plots these inequalities on a u-v1 graph to show the feasible region.

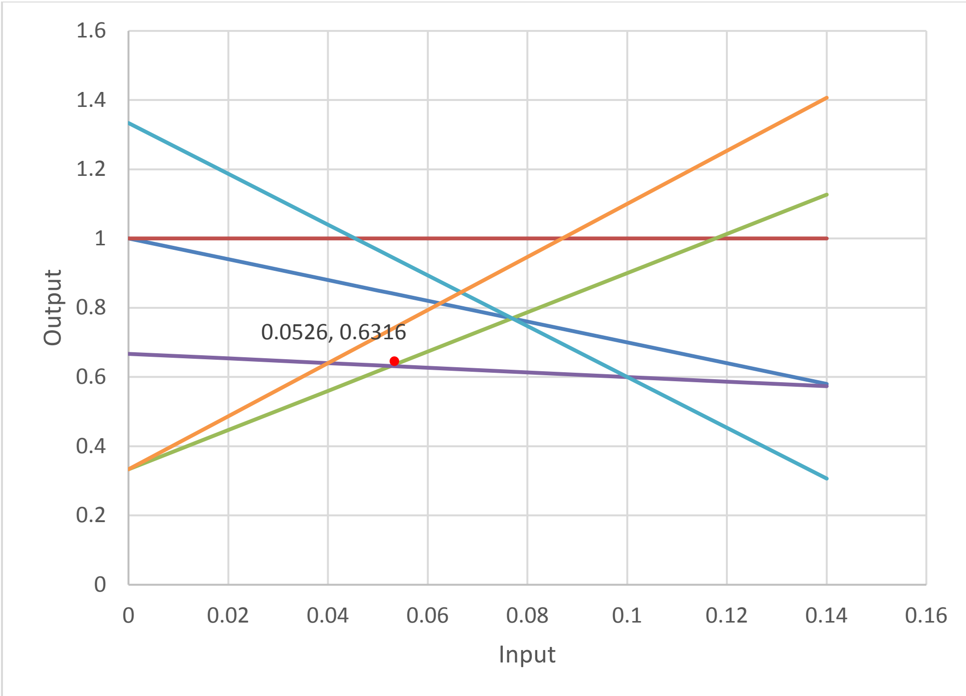

Figure 3 Graphical Solution of Example Model

The value of the maximum point in the model for DMU B (as shown in Figure 3) in the region within the inequalities is shown as (0.0526, 0.6316), a value that can be double checked by manually calculating efficiency score using the formula as well. The same method can be used to solve the rest of the DMUs, giving us the results shown in Table 3, where DMU A and B have efficiency scores of 85.71 and 63.16 percent, respectively, while the rest of the DMUs have 100 percent efficiency scores.

Table 3 Efficiency Scores for the DMUs in the Example Model

DMU	Input 1	Input 2	Output	Efficiency Score	Input 1/Output	Input 2/Output
A	4	3	1	0.8571	4	3
B	7	3	1	0.6316	7	3
C	8	1	1	1	8	1
D	4	2	1	1	4	2
E	2	4	1	1	2	4
F	10	1	1	1	10	1

Plotting the normalized values of Input 1 versus Input 2 and connecting points E, D, C, and F in the graphical solution shows the efficiency frontier of this DEA model, as shown in Figure 4.

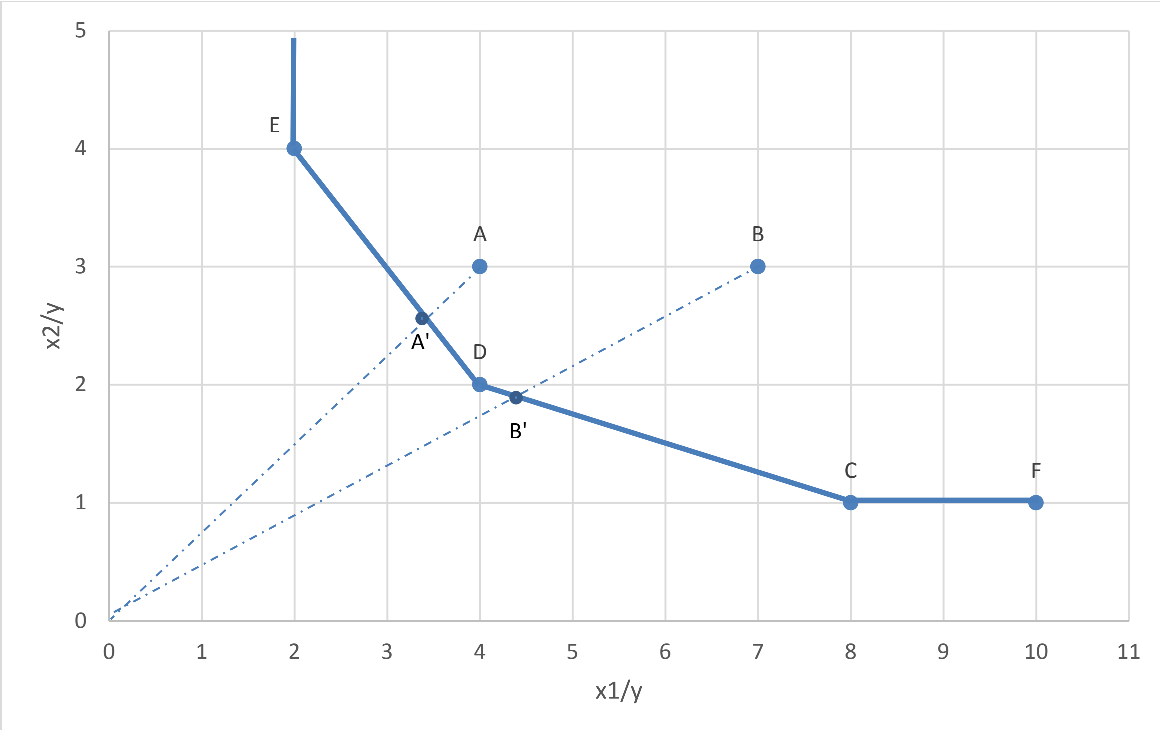

Figure 4 Efficiency Frontier

Figure 4 shows the efficiency frontier of the DEA model. It shows DMUs E, D, C, and F located on the frontier as efficient DMUs. DMU A and DMU B are not on the frontier, and their efficiency scores can be calculated from the ratio of the distance between (0,0) to the intersects of OA/OB with the frontier (OA'/OB') and the distance of OA/OB. When calculated, the two values show efficiency scores of 0.8571 for DMU A, and 0.6316 for DMU B. This is consistent with the efficiency scores from the calculation, which are shown in Table 3.

This Study Versus Other Research

The method described above is commonly used in the typical application of DEA modeling to identify and compare efficiencies and performances of DMUs within a jurisdictional area. Ozbek et al. (2010) used DEA analysis of bridge maintenance to identify the effects of parameters in a maintenance cycle and determine efficiencies of DMUs, which are multiple counties in the state of Pennsylvania. Results from this 2010 study show the relative efficiencies of bridge maintenance in 21 DMUs. The analysis was able to identify which counties are performing most efficiently at 100 percent efficiency scores, and on the other hand identified the counties that have not been performing efficiently, with one county in particular receiving an efficiency score as low as 18 percent (*11*).

In a 2012 study, London et al. used DEA modeling to compare efficiencies of the Transportation Performance Index (TPI) between states in the United States. TPI is a performance measures for transportation infrastructure that is designed to reflect the infrastructure's ability to meet the needs of businesses, and therefore is highly correlated with economic performance indicators. This 2012 research focuses on exploring the true relationship of TPIs between states while taking into account the effects of environmental factors, such as population growth and VMT. By using DEA to examine the effect of adding and removing these environmental factors, the study was able to compare the relative efficiencies of TPI between the states (*12*).

Wakchaure and Jha (2011) discussed how funding allocations for bridge maintenance in India are generally based on a bridge health index. In this 2011 study, Wakchaure and Jha applied a DEA-based method to compare efficiencies of the maintenance of individual bridges. The result is an efficiency-based ranking of bridges which provides the information needed for the researchers to propose reallocation of bridge maintenance funds to produce higher overall efficiency scores of all bridges (*13*).

As shown in the examples above, several studies utilized the DEA method to identify infrastructure maintenance efficiency and improve maintenance investment strategies. All three examples show the usage of DEA modeling to compare maintenance processes between DMUs within a specific jurisdictional area. One study compares the efficiency of maintenance of individual bridges, the other study compares maintenance efficiencies of bridges among counties within a state, and the third study compares maintenance efficiencies of the transportation infrastructure in different states that have similar characteristics. In all of the examples, the researchers were able to determine the efficiency scores of all the DMUs and rank these peer DMUs based on their efficiency scores. These results are useful for the purpose of benchmarking— comparing how DMUs perform compared to each other—which is helpful in system-wide maintenance decision-making.

In this study, instead of comparing multiple DMUs efficiency scores to determine which DMU performs best, the analysis is decentralized and focuses on individual DMUs to identify parameters that effect the efficiency scores the most in each individual DMU. The reason for doing this is to identify potential patterns in the parameters within the individual DMUs. This can help maintenance administrators in targeting specific parameters to improve maintenance efficiency in a particular DMU. This study observes the different combinations of parameters of an individual DMU throughout several maintenance cycles, observes the efficiency scores of a given DMU and how the parameter data are in those years, and identifies the parameters that appear to have significant effects, either positive or negative, on the DMU's efficiency scores.

Each time a DEA model was run in this study, it focused on the maintenance performance of a single asset in an individual DMU, and the result of each model was unique to that DMU. Naturally, the significant parameters will vary depending on the type of asset being analyzed, and may also vary between DMUs with different special characteristics. This decentralized analysis approach also means that there is no need to consider variations in external factors that may affect maintenance performance in each DMU location when including parameters in the model. Assuming that there have not been any changes in the given DMU's maintenance practice, things like maintenance scheduling, specific local policies and regulations, and similar factors are regarded as uniform across the DMUs. The only exception is the dollar value of expenditures, which must still be adjusted because data from different years are used.

The difference in the typical use of DEA modeling and how it is being used in this study is illustrated in Figure 5. The left side of Figure 5 shows the typical use of DEA modeling in comparing three different DMUs (A, B, C) with their own values of input and output parameters in the year 2013. The right side of Figure 5 shows DEA modeling as it is performed in this study, comparing DMU A and its set of input and output parameters in three different years (2011, 2012, 2013).

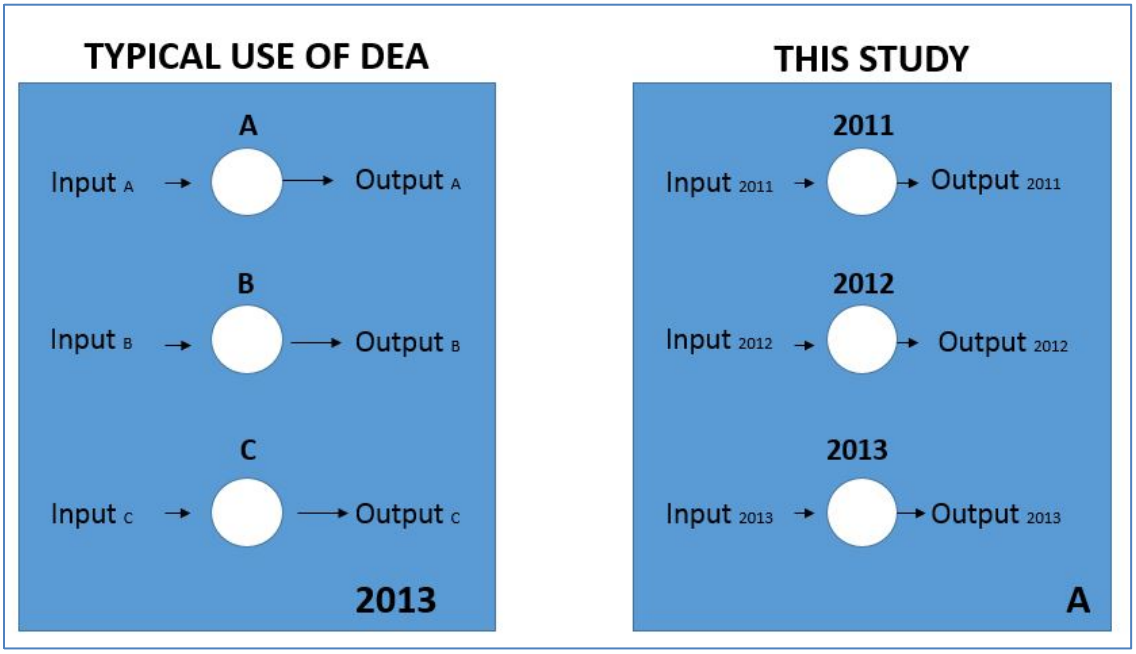

Figure 5 Typical Use of DEA vs. This Study

In summary, we are using decentralized analysis in this study because the goal is not to identify the most efficient and inefficient production entities or DMUs, but to observe individual DMUs and identify parameters that have the most significant effect in their efficiencies. In short, this method:

1. Compares the efficiency of maintenance performance of individual DMUs concerning a particular type of transportation asset.
2. Observes historical data (year n, n+1, n+2, n+3…) of individual DMUs and models it using DEA.
3. Identifies the years where a DMU performs most efficiently/inefficiently and recognizes the parameters that are significant, exposing how these parameters are affecting the efficiency of maintenance work on that DMU.

After the parameters significantly affecting the efficiency of maintenance work are identified, the case studies were developed by creating sensitivity analysis scenarios, varying the values of these parameters, and observing the different ways these parameters affect the efficiency scores of the DMUs. Note that because the analysis being used is based on comparative analysis, the term ‘efficient’ and the values of efficiency of a DMU in this research simply show the performance of each DMU in comparison with other DMUs in a particular model, which in this study means the same DMU, but at different years. A particular year where an observed DMU has an efficiency score of 100 percent does not imply a ‘perfect’ maintenance strategy that year; instead it should be read as “the best this DMU can do, compared to the other observed years in the model, as a result of the parameters included.” On the other hand, a lower score for a particular year simply means that the DMU could do better compared to other years.

5. Case Studies and Analysis

Preparation

The formulation of DEA in this study is based on the assumption that an increase in input parameters results in an improvement in the measured condition at the end of a maintenance cycle. An input-oriented DEA formula, the CCR model, was then used to compare technical efficiencies of the DMUs being analyzed. This input-oriented DEA method determines the relative efficiency measure for a DMU by maximizing the ratio of weighted outputs to inputs. As explained in the previous section, this study focuses in temporal comparisons of efficiencies of maintenance work of transportation infrastructure assets in one location, based on available historical data.

The results of running the DEA models is a set of efficiency scores for each DMU. An efficient DMU with 100 percent efficiency score means in that particular year, that DMU is performing at its peak performance. On the other hand, lower efficiency scores reflect potential improvement, based on the performance of this same DMU in other years.

While it is possible to manually solve simple DEA models that only have a few parameters using a spreadsheet, to improve speed and accuracy in iterating DEA solutions with many parameters, DEA-specific software is used for the case studies. OSDEA-GUI is a free and open-source DEA solver (*14*). Table 4 shows example results from the DEA modeling procedure used in this study. Running a DEA model using OSDEA-GUI yields the identification of efficient DMUs and inefficient DMUs (which is shown by the percentage numbers under 'Efficiency Score' column) from the set of DMUs in the model.

Table 4 Example of Result Table

DMU	Efficiency Score (%)	Efficient
A	100	Yes
B	100	Yes
C	*90.3*	
D	100	Yes
E	*95.1*	
F	100	Yes

Region Level Bridge Maintenance Models

This study uses region-level bridge maintenance data in Wisconsin from 2007 to 2013. This data set was gathered from multiple sources, including Federal Highway Administration's National Bridge Inventory (NBI) and the Wisconsin DOT. These data are: maintenance year as decision making unit (DMU), average sufficiency rating (SR), maintenance expenditures in dollars (Exp), average winter severity index (WSI), average daily traffic (ADT), and total bridge deck area in square feet (Area).

To develop the case studies, the data was run through the DEA modeling program, producing a set of efficiency scores and projection values for all of the DMUs, which in this case are all five regions in Wisconsin from 2007 to 2013, as shown in Table 5. The calculation then begins by running the bridge maintenance parameter data on each of the five regions in Wisconsin through the DEA modeling software, one model for each region, for a total of five region-level models. The results from these models are then used to establish the baselines for the case studies. These baselines show the important data points in the group of DMUs we are analyzing, which includes information on the year(s) a particular DMU is shown as performing efficiently and/or inefficiently and detail information about the parameters during those times. The baseline values are then used as a starting point for the sensitivity analysis scenarios.

The parameter data of bridge maintenance in 2007 to 2013 from the five Wisconsin regions (North Central, North East, North West, Southeast, Southwest) are shown in Table 5. After running the parameters as input data for the DEA solver program, the years where the DMUs (regions) perform inefficiently were identified. The highlighted rows in Table 5 show the years where a particular region received efficiency scores less than 100 percent, with the scores shown in the right-most column.

Table 5 Summary of Input/Output Parameters and Efficiency Scores From All Five Regions

Model (Region)	Year	SR	Exp	WSI	ADT	Area (sqft)	Efficiency Score
Model 1 (NC)	2007	86.24	$1,400,084	32.4	2852	622,539	100%
	2008	85.72	$1,458,337	41.2	2721	630,134	100%
	2009	85.3	$1,245,623	43	2778	679,355	100%
	2010	89.17	$1,948,726	28.7	2935	702,873	100%
	2011	*89.01*	*$1,628,757*	*43.4*	*2983*	*708,491*	***95.1%***
	2012	89.42	$1,662,258	28.5	3261	760,098	100%
	2013	*89.89*	*$1,680,124*	*42.5*	*3220*	*758,977*	***90.4%***
Model 2 (NE)	*2007*	*83.45*	*$1,209,670*	*26.7*	*5754*	*1,065,168*	***96.4%***
	2008	*83.82*	*$1,228,343*	*37.5*	*5479*	*1,074,494*	***96%***
	2009	*84.07*	*$1,400,832*	*35.2*	*5448*	*1,102,952*	***93.8%***
	2010	91.72	$1,219,578	24.6	5520	1,128,295	100%
	2011	91.48	$1,061,920	33.4	5289	1,132,785	100%
	2012	91.82	$1,270,970	22.1	5502	1,151,897	100%
	2013	91.83	$1,468,498	32.2	5323	1,164,700	100%
Model 3 (NW)	*2007*	*81.56*	*$2,344,144*	*28.7*	*2843.37*	*1,263,530*	***96.5%***
	2008	82.94	$2,320,468	35.7	2729.26	1,266,875	100%
	2009	83.3	$2,306,812	36.16	2739.73	1,271,801	100%
	2010	87.41	$2,312,113	27.98	2955.43	1,280,241	100%
	2011	87.23	$2,139,550	42.22	3106.44	1,276,808	100%
	2012	87.62	$2,288,453	25.61	3270.54	1,276,071	100%
	2013	87.53	$2,200,258	41.37	3289.1	1,275,324	100%
Model 4 (SE)	2007	83.96	$2,714,928	24.2	9566	1,620,666	100%
	2008	84.45	$2,941,039	35.6	9216	1,638,057	100%
	2009	*84.19*	*$3,373,494*	*31.59*	*9377*	*1,715,339*	***95.5%***
	2010	87.17	$2,981,787	22.31	9561	1,723,704	100%
	2011	87.12	$3,456,450	30.73	9047	1,698,459	100%

Model (Region)	Year	SR	Exp	WSI	ADT	Area (sqft)	Efficiency Score
	2012	87.01	$4,580,352	17.92	8600	1,717,460	100%
	2013	86.94	$3,704,762	27.63	8713	1,737,958	100%
Model 5 (SW)	*2007*	*83.9*	*$4,155,414*	*26.7*	*3807.57*	*1,461,134*	***98%***
	2008	*83.79*	*$3,949,598*	*35.1*	*3665.14*	*1,465,243*	***98.8%***
	2009	*83.62*	*$3,538,881*	*31.19*	*3724.66*	*1,469,348*	***97.4%***
	2010	87.84	$3,706,061	25.72	3797.5	1,499,304	100%
	2011	*87.71*	*$3,328,883*	*35.02*	*3813.71*	*1,521,513*	***99.9%***
	2012	87.58	$3,448,195	22.3	3887.62	1,550,151	100%
	2013	88.36	$2,638,735	33.56	3874.58	1,565,698	100%

As shown in Table 5, the model for the North Central (NC) region identifies the two years when bridge maintenance were performed inefficiently: 2011 (95.4 percent efficiency) and 2013 (90.4 percent). In the North East (NE) region, the model identifies three inefficient years: 2007 (96.4 percent), 2008 (96 percent), and 2009 (93.8 percent). In the Northwest (NW) region, the model identifies one inefficient year: 2007 (96.5 percent). In the Southeast (SE) region, the model also identifies only one inefficient year: 2009 (95.5 percent). The Southwest (SW) region has the most inefficient years with four: 2007 (98 percent), 2008 (98.8 percent), 2009 (97.4 percent), and 2011 (99.9 percent).

Based on these five region-specific models, we now have baseline values for developing the cases. The cases themselves are developed by focusing on different aspects and parameters in the maintenance cycle that are important in the maintenance process. The first case focuses on observing the effect that fluctuations of expenditures have on the efficiency scores, as shown by the results of DEA modeling. The second case focuses on the changes in efficiency scores of maintenance cycle when sufficiency ratings are low. These two cases serve as examples of potential use of this method. Depending on what aspects and parameters we want to focus on, many other cases could be generated.

For the cases in this study, the sensitivity analysis technique was applied by gradually increasing or decreasing the values of parameters, and DEA models were run for each iteration to record the variation in efficiency scores. In each case, different parameters were chosen to gradually increase or decrease.

Case 1: Expenditures

In the first case, the investigation focused in the sensitivity of bridge maintenance efficiencies in the DMUs to variations in funding. From the baseline data, one set of parameter data from each region was selected from the year where that region had efficiency scores less than 100 percent, representing an inefficient DMU. These data are: NC 2013, NE 2009, NW 2007, SE 2009, and SW 2009. Hypothetical DEA models were then run for these five data sets for different levels of expenditures, ranging from 70 percent to 115 percent of the original expenditures. The results of the DEA modeling of these DMUs are shown in Table 6.

Table 6 Efficiency Scores at Different Levels of Expenditures

	Percentage of Expenditure	DMU (Region Year)				
		NC 2013	NE 2009	NW 2007	SE 2009	SW 2009
Increasing Expenditure	115%	89.80%	93.80%	96.50%	95.50%	97.10%
↑	110%	89.90%	93.80%	96.50%	95.50%	97.10%
	105%	90.10%	93.80%	96.50%	95.50%	97.10%
Original Expenditure	100%	90.40%	93.80%	96.50%	95.50%	97.40%
	95%	91.00%	93.80%	96.90%	96.20%	98.00%
	90%	92.10%	93.80%	100.00%	97.50%	98.50%
↓	85%	96.00%	93.80%	100.00%	99.30%	99.10%
Decreasing Expenditure	80%	100.00%	94.00%	100.00%	100.00%	99.70%
	75%	100.00%	94.30%	100.00%	100.00%	100.00%
	70%	100.00%	99.50%	100.00%	100.00%	100.00%

Table 6 shows that there are minimal changes in all of the DMUs when their expenditures are increased from 100 percent to 115 percent the original. In fact, the efficiency scores for NE, NW, SE, and SW regions seem to have achieved their minimum at 93.8 percent, 96.5 percent, 95.5 percent, and 97.1 percent, respectively. The only exception is the NC region, where its efficiency scores keep decreasing when expenditures are increased to 105 percent and 110 percent, and finally reaches its minimum efficiency scores at 115 percent of the original expenditure. This result shows that besides the NC region, all the other DMUs have maintenance systems that are not sensitive to increasing amounts of expenditures.

On the other hand, Table 6 shows a significant increase in efficiency scores across all the DMUs when expenditures in the DMUs are reduced in steps of 5 percent to 70 percent. Table 6 also shows that the DMUs achieve 100 percent efficiency scores at different levels of expenditures, so while they all seem to be relatively sensitive to reduction of expenditures, the sensitivity varied across the DMUs. NC region achieves 100 percent efficiency score at 80 percent expenditure, while NW, SE, and SW regions achieve 100 percent efficiency scores at 90 percent, 80 percent, and 75 percent expenditures, respectively. These sensitivity differences explain how slightly different maintenance practices and policies between DMUs may have caused them to react differently to changes in expenditures. One DMU that stands out from Table 7 is the NE region, where it only achieves 100 percent efficiency score at lower than 75 percent of its actual expenditure (99.5 percent at 75 percent expenditure). This shows that the NE region is the hardest region to manage. Not only is its efficiency the lowest among the DMUs, it was confirmed that it would only be considered efficient when its sufficiency rating is maintained while lowering its maintenance investment to 70 percent of the actual expenditure, and that is not an easy thing to do.

Table 6 shows that adding more money into the established maintenance procedures for these DMUs does not significantly affect the efficiency for most of the DMUs, while reducing the amount of funds spent have a noticeable positive effects on the efficiency of the DMUs. In fact, most of the time a slight increase will get a DMU to its maximum efficiency score. Figure 6 shows a graphical representation of the results from Table 7. The horizontal axis represents the variety of expenditure percentages compared to the actual expenditures, while the vertical axis shows the efficiency scores of the DMUs for each of the funding levels. As shown in Figure 6, relatively flat lines (representing constant efficiency scores) are shown from expenditure percentages ranging from 100 to 115 percent for most the DMUs, while a variety of relatively steep lines represent the increase in efficiency scores in the DMUs when expenditures are reduced. Note that all of this includes the assumption that all other parameters stay the same including SR, therefore keeping the quality of maintenance consistent.

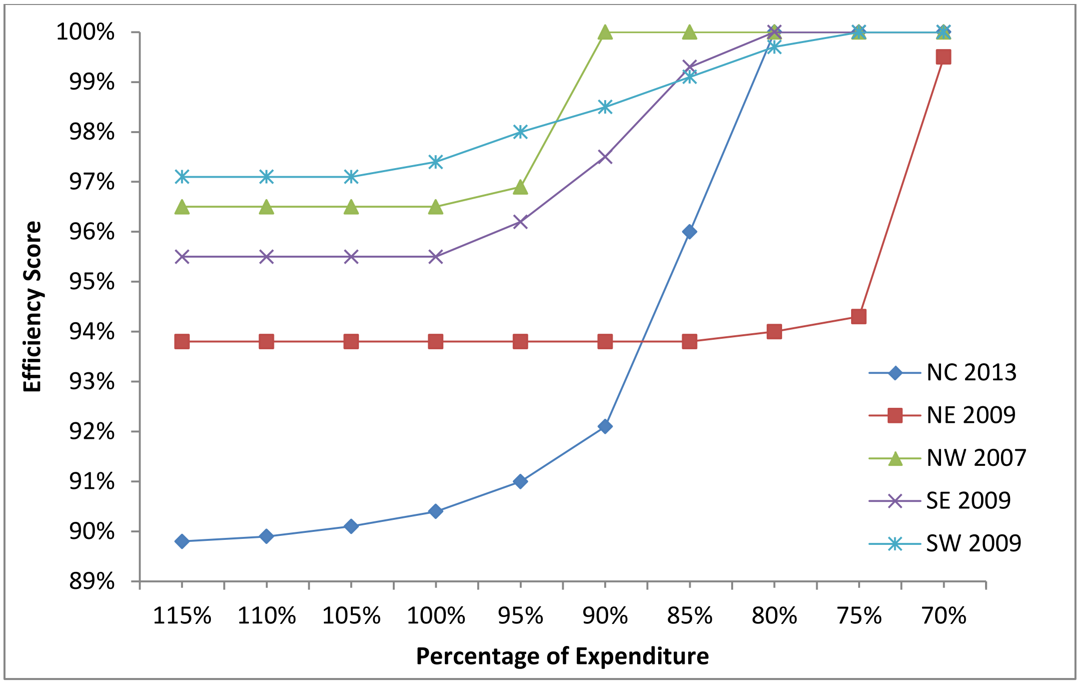

Figure 6 Graphical Representation of Efficiency Scores at Different Levels of Expenditures

In Figure 7, we can see that the curve connecting the plots for each DMU represents the degree of sensitivity in efficiency scores when we gradually increase or decrease expenditures. With flat and steep curves showing insignificant and significant effects on efficiencies in these DMUs, we can see that the maintenance process of a DMU is at optimal performance when located at the lowest possible point on its curve. Increasing or decreasing expenditures from this point resulted in the lowest rate of increase or decrease of efficiency scores. This optimal point is the local minimum of that curve, which can be calculated by deriving the curve's polynomial function. To find this optimal point, third degree polynomial functions were fitted on the scatter plot created by the models in Case 1. These functions show the predictive formula of how variation in expenditures affects the efficiency scores. Figure 7 shows the fit and the equations representing these functions.

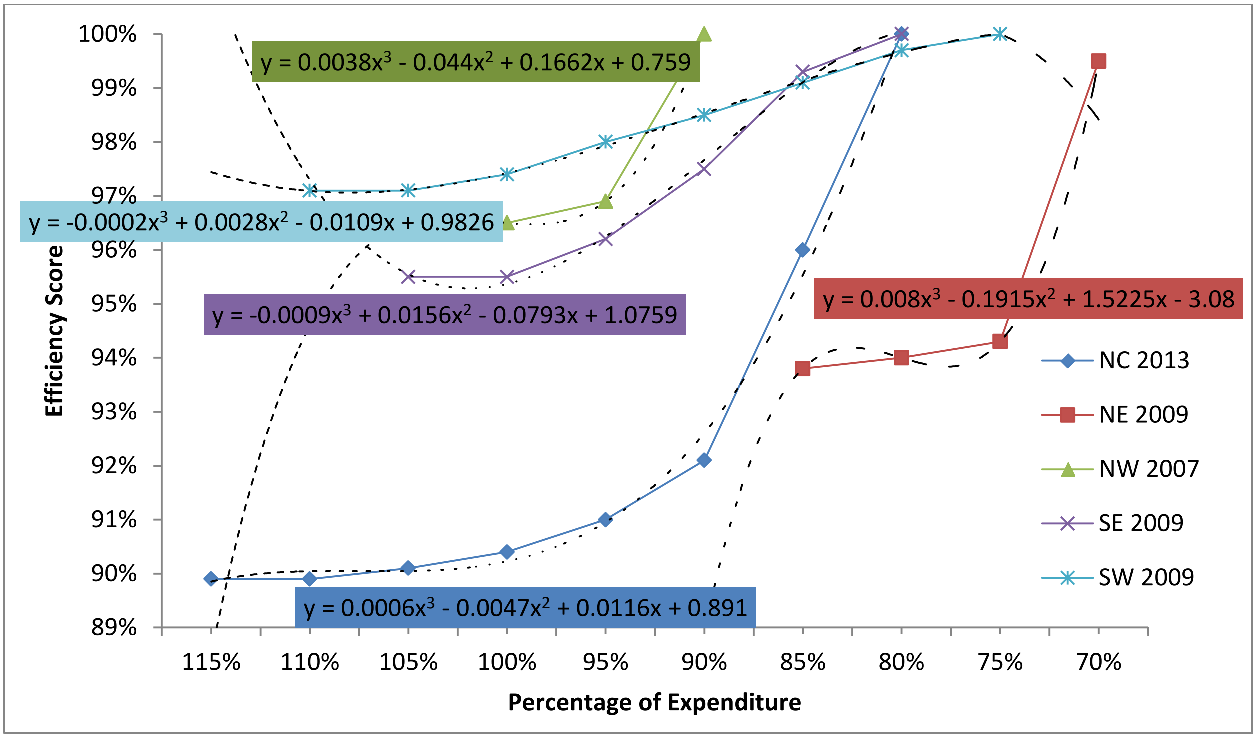

Figure 7 Third Degree Polynomial Fit of Case 1

As previously mentioned, taking the local minimum of each curve gave us the point where reducing or increasing expenditures would not give that DMU a significant advantage or disadvantage. Knowing these optimal points could help in making decisions related to distribution of maintenance funding. The optimal points for the DMUs in Case 1 are shown in Table 7.

Table 7 Local Minimum of Trendline in DMUs and Differences for Case 1

DMU	3rd Degree Polynomial Fit	Local Minimum (Optimal)	Actual Efficiency Score	Differences
NC 2013	$y = 0.0007x^3 - 0.0059x^2 + 0.0176x + 0.8821$	89.97%	90.38%	0.41%
NE 2009	$y = 0.008x^3 - 0.1915x^2 + 1.5225x - 3.08$	93.84%	93.77%	-0.07%
NW 2007	$y = 0.0038x^3 - 0.044x^2 + 0.1662x + 0.759$	96.21%	96.53%	0.32%
SE 2009	$y = -0.0009x^3 + 0.0156x^2 - 0.0793x + 1.0759$	95.04%	95.45%	0.41%
SW 2009	$y = -0.0002x^3 + 0.0028x^2 - 0.0109x + 0.9826$	96.96%	97.43%	0.47%

Table 7 shows that the DMUs have been performing generally well. The differences between the actual efficiency scores achieved and the optimal efficiency scores calculated from the formula range from 0.07 to 0.47 percent. The lowest difference is 0.07 percent in the NE region in 2009, where the optimal efficiency score is only 0.07 percent higher than the actual efficiency score. This shows that this DMU was able to get 0.07 percent more efficiency score than optimal, with spending a little more money than needed. The highest difference is in the SW region, also in 2009. In this region, the optimal efficiency score is 0.47 percent lower than the actual efficiency score. This shows that had this region spent a little less, it could achieve a little more efficiency without sacrificing the quality of maintenance with a lower Sufficiency Rating. Having said that, all these differences show numbers that are less than 0.5 percent, which cannot be considered significant.

Case 2: Sufficiency Rating

The second case investigates the changes in efficiency scores of the DMUs when the Sufficiency Rating is low. This approach was taken to gather information regarding the efficiency of the DMUs when bridge conditions are low and declining. For the purposes of this case, one DMU was picked from each year where a DMU has the lowest sufficiency rating from what is considered an efficient DMU (having a 100 percent efficiency score). The selected DMUs are from 2008 in NC region, 2011 in NE region, 2008 in NW region, 2007 in SE region, and 2012 in SW region. DEA models were then run with the data from these five DMUs by varying the original SR values, starting from the actual value and decrementing it by 2 percent each time until it reaches 76 percent of its original value. Table 9 shows the efficiency scores in the five selected DMUs after bridge conditions keep deteriorating.

Table 8 Fluctuation of Efficiency Scores when Sufficiency Rating Declines

% Sufficiency Rating	NC 2008	NE 2011	NW 2008	SE 2007	SW 2012
100%	100%	100%	100%	100%	100%
98%	100%	100%	98%	100%	100%
96%	99.2%	100%	96%	100%	100%
94%	97.2%	100%	94%	99.4%	100%
92%	95.1%	100%	92%	97.3%	100%
90%	93%	100%	90%	95.2%	100%
88%	91%	100%	88%	93.1%	100%
86%	88.9%	98.5%	86%	91%	98.9%
84%	86.8%	96.2%	84%	88.9%	96.6%

% Sufficiency Rating	NC 2008	NE 2011	NW 2008	SE 2007	SW 2012
82%	84.8%	93.9%	82%	86.7%	94.3%
80%	82.7%	91.6%	80%	84.6%	92%
78%	80.6%	89.3%	78%	82.5%	89.7%
76%	78.6%	87%	76%	80.4%	87.4%

Figure 8 shows the graphical representation of models from Case 2. The horizontal axis shows the change in percent sufficiency rating, where 100 percent is the actual SR value from the data, which in the experiment were varied gradually down to 75 percent of those values. The vertical axis shows the efficiency scores for each model. The varied reactions by the DMUs show that each DMU has a different turning point where its efficiency score gets reduced by worsened condition. NW region is shown as one DMU without any flexibility, as even a 2 percent reduction in condition reduced its efficiency to 98 percent. The SW region is shown as the DMU with most flexibility; at a 14 percent reduction in condition it only lost 0.1 percent of its efficiency. The NC region is right behind it, with a 14 percent worse condition making it lose 0.5 percent efficiency. Another interesting observation is that even though the sensitivities of the DMUs vary and their efficiency scores start to decline at different levels, the decline of efficiency scores all shown to be linear against condition.

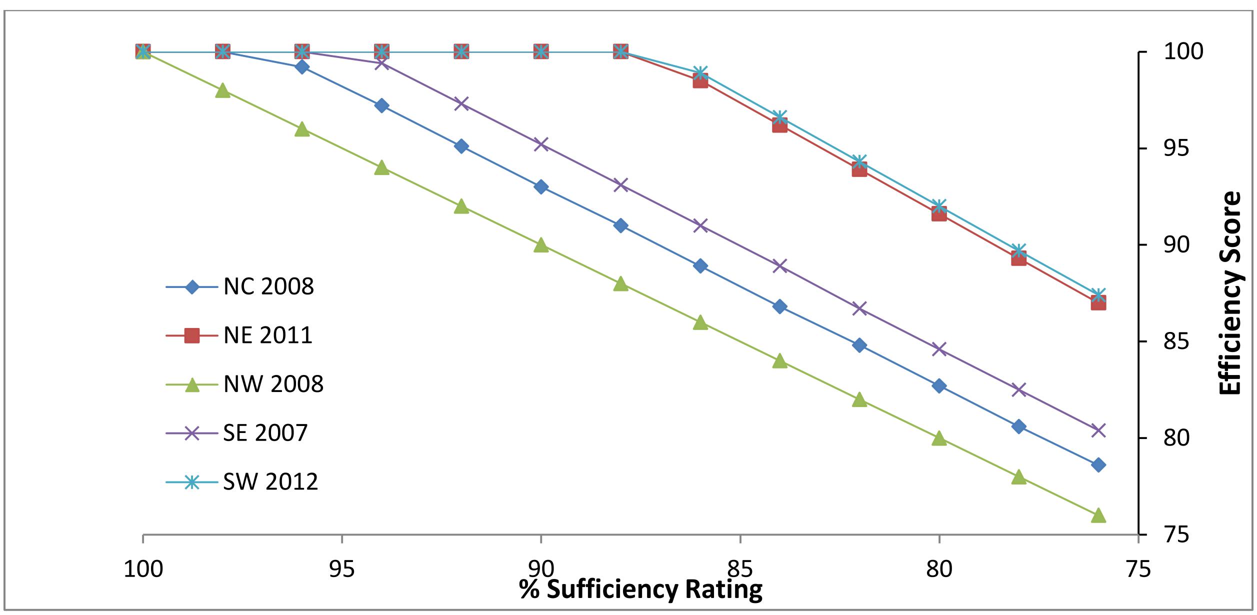

Figure 8 Graphical Representation of Case 2

Case 2 investigates the sensitivities of efficiency scores in the DMUs when the Sufficiency Rating is low. Observing efficiency sensitivities on DMUs that are shown to be efficient simulates the situation where bridge conditions are declining on a system known to be working efficiently. The result confirms that the efficiency scores of the DMUs have different sensitivities and react differently to declining conditions. The NW region's efficiency is reduced 10 percent in a 10 percent worse condition, while the SW region still performs excellently at 100 percent efficiency even in a 10 percent worse condition. Having said that, when efficiency scores decline, it is shown to be linear against a decline in the sufficiency rating. This means that in this set of DMUs the effect of each percent of decline in sufficiency rating is a one percent reduction in efficiency.

Analysis Summary

These case studies produced the following results:

1. There are different rates of change in efficiency scores in the DMUs when they are affected by changes in expenditures. It is known that the DMUs being observed do not have identical maintenance practices and policies, which confirms that each DMU has different sensitivities against expenditure and that a shift in some parameters may affect the DMUs differently.

2. Fitting a third degree polynomial equation on the curve of efficiency scores at different levels of expenditures allowed us to estimate the optimal point of expenditures. Increasing or decreasing expenditures from this point resulted in the lowest rate of increase or decrease of efficiency scores.

3. Some models show that there is a peak performance point in some DMUs where improving expenditures or other input parameters hit a point of diminishing return and simply no longer affect efficiency. DMUs on peak efficient performances are unaffected by certain

parameter changes. With regards to expenditures, allocating more funds to these DMUs will not make these DMUs perform any more efficiently.

4. In some cases there may not be new information (i.e., sensitivities are different among regions) that we can gather regarding the DMUs, but even a single piece of information about efficiency scores at each DMU themselves is useful for recognizing an individual DMU's characteristics and can be used to develop more studies regarding the efficiency of maintenance investments.

5. Depending on the needs, more scenarios can be developed to test specific situations and/or other infrastructure asset types that a maintenance administrator would like to investigate. The cases discussed in this research presented situations focusing on expenditures and bridge conditions. Other scenarios may focus on pavement or other features.

6. Information collected from the case studies can be compiled to create a recognizable identity for each DMU and asset type, making it easier for maintenance administrators to make maintenance investment decisions in the future.

6. Summary of Findings

The primary goal of this study is to present an alternative way to analyze the process of maintenance for transportation infrastructure asset management, and to provide maintenance administrators with valuable information that could help them make better decisions in their maintenance strategy that are consistent with the spirit of performance-based decision-making. This was done by identifying the most significant parameters that affect the efficiency of the maintenance process, analyzing on how these parameters effect efficiency, and then discussing how to use the results to guide improvements to maintenance investment strategies. It was shown that running a CCR-based DEA model on specific DMUs provides us with the information we need regarding the parameters that matter the most in the efficiency of the system and the maintenance procedures being performed in these DMUs.

Parameters and Models

As we have already discussed, this method is highly dependent upon the parameters used in the models, making parameter selection a crucial part of the process. Because of this, the models used in this study can always be improved by investigating more parameters that may be relevant and reviewing potential additional parameters when data for significant parameters became available. Maintenance administrators interested in applying this method need to be open to possibilities and consider adding, removing, or replacing parameters that are included in the models as needed.

For instance, on bridges, the proper bridge age (number of years from when the bridge entered into service or since its latest major rebuild/rehabilitation) might be relevant to maintenance efficiency. The Sufficiency Rating (SR) does not take into account rehabilitation or new construction dates, and the proper age of the bridge potentially has a significant effect on the deterioration rates of the elements. If this data is available and it can be considered as a parameter that affects maintenance efficiency, then it may need to be included in the model. Another example is the bridge's Sufficiency Rating (SR) target value. In the emergence of performance-based maintenance, some states may have set periodical target values of SR for their bridges. The reason why it is important for target to be included will be detailed in the Follow Up section below, but if target SR values for each bridge are available, or even if what is available are only composite SR target numbers for bridges in the jurisdictional area (counties, regions, etc.), then these also need to be included in the models. On the other hand, states with relatively consistent temperatures that do not experience harsh winter weather most likely do not have a Winter Severity Index and do not need to include it in the models. They may include a different weather-related parameter that has relevance to the location, if such parameter has been proven to affect maintenance efficiency.

The parameters, when setup, are used to develop Data Envelopment Analysis (DEA) models based on CCR, one of the original DEA models. This particular model focuses on the idea that a DMU is to be rated as fully efficient if the performances of other DMUs in the group do not show that some of their inputs or outputs can be improved without worsening some of its other inputs or outputs. Based on this, the CCR model is then solved by maximizing the sum of weighted output divided by the sum of weighted input. This CCR-based DEA model is considered to be most appropriate for this this study, however there are other variations of the DEA model that can also be used, depending on the types of cases and scenarios we are interested in investigating. Follow-up studies for investigating other types of DEA modeling that are more appropriate in these scenarios will be helpful.

The Results

The results of this study show that the characteristics of each DMU allow us to understand how each DMU reacts to certain changes in selected parameters in each cycle of their maintenance periods. The cases developed in this study are not fully inclusive, and were meant to be examples of how to use this method to gain information about the DMUs and their sensitivities to the parameters that were selected. This same method could be used to develop a variety of different cases that focus on different things, depending on what specific characteristics maintenance administrators may want to find out about the DMUs in their systems. Administrators may want to look specifically at situations when funding is low, for instance, and create a specific case for this situation.

In the cases discussed in this study, we were able to show interesting results from the DMUs related to different issues. We identified the different change rates in efficiency scores of the DMUs after a change in certain parameters. We also discovered how certain DMUs have been operating at their optimal efficiency, which is a valuable information that we can take further into learning more about what these DMUs have done right, and possibly to help make an effort to implement these methods for other DMUs. We also found DMUs that are unaffected by certain parameter changes. This means if there is a question about how a DMU may improve its performance, we know not to make changes in the parameters that we know would not make any improvement in the efficiency. From certain modeling process and case studies we could also derive a lot of information about the DMUs and asset types simply from the knowledge of how sensitive each of them are to changes in certain parameters. This information can be crucial for maintenance administrators in making their maintenance investment decisions for the next maintenance period. It is especially useful to ensure that whatever decisions they make will not be ones that ultimately reduce the efficiency of the system.

7. Implementation Plan and Follow Up

There are three potential ways to implement the method used in this study:

1. Evaluating efficiencies of prior work

The method used in this study uncovers the efficiencies and thus history of performance of maintenance practices for a set of DMUs. Running historical data through this modeling process gives us a greater understanding of how efficient maintenance work has been, allows us to identify inefficient DMUs, and provides the information needed to study the ways to improve the system. Maintenance administrators can use this data to review the efficiency of maintenance practices in these DMUs. This will give maintenance administrators a chance to evaluate the decisions—budget allocations, work distributions, and project selections—from prior maintenance cycles and assess all decisions made in these cycles.

For example, a maintenance administrator collect information about efficiencies of prior work from the models and compare the DMUs when they performed efficiently. As each DMU's characteristics differ, it would be useful to find out what is different (or similar) between the DMUs at the time when they are all performing at their best. For example, in Table 4 above, we see that the North Central region is performing inefficiently in 2011 and 2013, and has been performing efficiently in all the other years since 2007. At the same time, the North East region performed inefficiently from 2007 to 2009, but did perform efficiently from 2010 to 2013. If we compare the two DMUs in 2010 and 2012, where they both performed efficiently, we discovered that considering the larger area and higher traffic levels in the NE region, in both years the NE region produced a better SR scores than the NC region, as shown in Table 11. A maintenance administrator can use this information to better understand the regions and how they perform as an efficient system.

Table 9 Comparison of Bridge Parameters in the NC and NE Regions in 2010 and 2012

Region	Year	SR	Exp	WSI	ADT	Area
NC	2010	89.17	$1,948,726	28.7	2935	702,872.78
NC	2012	89.42	$1,662,258	28.5	3261	760,097.80
NE	2010	91.72	$1,219,578	24.6	5520	1,128,295
NE	2012	91.82	$1,270,970	22.1	5502	1,151,897

2. Planning for subsequent maintenance cycles

The case studies showed that each different type of transportation asset in each DMU may have a significantly different reaction and sensitivity to changes in parameter values. Every asset type is different, and each DMU may have something specific that only happens in that particular location that differentiates its maintenance process. It will show what work needs to be done to achieve better efficiency score, thus higher performance. Basing the decision-making process on this information helps maintenance administrators choose the most appropriate allocation, distribution, and selection strategies to ensure that maintenance is carried out in the most efficient way.

The result of this newly collected information can be used by maintenance administrators to help them plan subsequent maintenance cycles. Knowing what parameters have the most significant effect on efficiency allows maintenance administrators to focus on the things that matter the most. It allows them to always be well-informed before making decisions throughout the maintenance cycle, whether allocating the budget, distributing work, or selecting projects. After running the model and documenting these differences, the information collected will help maintenance administrators to develop short- and long-term plans for subsequent maintenance cycles.

3. Establishing efficiency guidelines to prepare for specific situations

Occasionally, there are significant changes in a DMU caused by a situation that is either planned (e.g., major highway construction/reconstruction or bridge repair) or unplanned (e.g., a natural disaster such as earthquake, etc.). Established parameter data from the relevant asset types and DMUs makes it possible for maintenance administrators to prepare for upcoming major changes.

In this case, the administrators can get the results from a particular maintenance cycle when the upcoming changes are expected, know how it will affect the normal maintenance cycle for that particular jurisdictional area, and prepare for the next maintenance cycle and correctly assign funds and resources to the places where they are most needed. In other words, with the information gathered from the DEA models, maintenance administrators can establish an efficiency guideline, knowing what would be the most efficient way to deal with planned or unplanned major changes in the parameters.

With an efficiency guideline established, maintenance administrators will know what to expect and the most efficient steps to take regarding resource allocation when there is a sudden budget cut, a drastic increase in traffic volume, major construction work, a natural disaster, or some other special circumstance.

Follow up

The method used in this study is highly dependent on selecting the significant parameters for each asset type, in each DMU, and at any level of jurisdiction (county, district, region, state, etc.). Consequently, the primary focus should be on the parameters, and it is essential to ensure that the parameters are accurate in representing the DMUs. On the other hand, this study shows that recognizing the differences between the DMUs and figuring out what makes each DMU unique is useful information for maintenance administrators. This supports the notion that each DMU is different and that to make sure that the maintenance process is as efficient as possible, investment strategies may need to be adjusted to fit the characteristics of each DMU. Finally, because this method uses historical data, this method works better in agencies that have implemented some type of performance-based system in their asset management programs.

As we discussed in the Analysis section, it is necessary to include target values as one of the parameters whenever possible. Targets start out as goals and represent a level of service that maintenance work needs meet, but in performance-based maintenance target also function as limits. That is, exceeding targets significantly is just as inefficient as when the results are significantly under the target because money spent on assets that over-perform significantly could have been allocated to underperforming assets. This is especially true in a system where it is impossible to fund transportation infrastructure assets so that they are all in perfect condition and meet all of their targets. Because there will be some assets that do not meet their targets, excessive spending that results in significantly exceeding targets is an inefficient use of funds. As such, target numbers also function as an 'expectation' level. This ultimately affects how administrators allocate resources, and therefore affects how maintenance work is performed. Because of this, target numbers are available, they should be included in the DEA modeling parameters. Maintenance administrators should also understand that because of the way the models are configured (inputs ultimately affect output), there may be situations where too high of an output might not be ideal for the overall system.

The results of a given modeling effort may vary from state to state based on how each state chooses to categorize and define its transportation infrastructure assets. It is important to continue to investigate different asset types and identify the proper asset types and parameters for the modeling process in each jurisdictional area. Further investigation may be required to identify potential additional parameters for each different asset type. If possible, it is best to have a periodical review of the assets and the parameters to determine whether changes are required to the way maintenance work is performed based on policy changes in different areas, new sets of relevant data, or simply because another year has passed and administrators want to make sure that they use the latest parameter data in the model. This situation calls for a revised set of parameters and a new round of modeling and analysis based changes in policy and data.

The cases in this study served as an example of the variety of scenarios that can help maintenance administrators to discover information useful for improving the efficiency of their maintenance system. As these scenarios are not inclusive, maintenance administrators are encouraged to develop different scenarios focusing on different aspects of maintenance. There are any number of possible scenarios such as to prepare when things are bad (low SR, low expenditures). This will greatly help administrators and provide the information that they need to adjust investment strategies so that they can more effectively maintain transportation infrastructure assets.

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Contacts

For more information:

Teresa M. Adams
University of Wisconsin-Madison
adams@engr.wisc.edu

NEXTRANS Center
Purdue University - Discovery Park
3000 Kent Ave.
West Lafayette, IN 47906

nextrans@purdue.edu
(765) 496-9724

www.purdue.edu/dp/nextrans