Accounting for Nonlinearity in the MCDM Approach for a Transportation Planning Application

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Abstract—We assess the impact of accounting for nonlinearity of selected value functions to improve the multiattribute utility theory approach for transportation planning applications. Research findings were obtained by conducting a case study for investigating and improving the project evaluation and selection with the collaboration of a state-level transportation agency. A methodology based on the analytic hierarchy process has been used for elicitation of the nonlinear value functions. It was found that employing nonlinear functions, as opposed to the commonly assumed linear scaling, even for only a subset of performance measures, had a significant impact in calculating the projects' index final scores, with changes ranging from 3% to 26%, possibly overturning the project selection. This paper highlights the importance that needs to be given to construct the value functions in decision-making problems and shows how the process could be improved by employing available tools properly.

Index Terms—Analytic hierarchy process, multiattribute utility theory (MAUT), multicriteria decision making (MCDM), value functions.

I. INTRODUCTION

TRANSPORTATION planning has always been characterized by the presence of an institutional framework that guides the planning process. There are also a variety of factors, such as political concerns, funding availability, agency jurisdiction, socio-economic and environmental issues, which act as constraints to transportation decision making. While historically, a majority of transportation decision making did not follow a formalized process, there has been a shift in recent times to apply performance measurement and decision-making processes.

Framing a transportation-planning problem using a multicriteria decision-making (MCDM) approach (with the aim of satisfying a set of objectives) is a reasonable way of addressing all the associated constraints and concerns. The ultimate aim of implementing a decision-making process is to allow the evaluation of alternatives on a common basis and enable sound decisions regarding future courses of action. This paper deals with such a decision-making methodology developed for a state-level transportation agency.

The topic of this paper fits within an overall research context involving the development of a user-friendly tool that incorporated sustainability concerns into the transportation planning process, with the use of performance measures that were evaluated to generate a "sustainability index" or "project index" value for use in decision making. The tool is currently being implemented into transportation planning practice by a state-level transportation agency.

Specifically, this paper highlights an aspect of the decision-making process, which is generally well known and understood theoretically, but often overlooked in practice and in particular, by transportation planning agencies; i.e., decisions are often taken assuming linear models. This paper presents a case study, in which first, the error due to nonlinearity is quantified to emphasize the importance of the use of more accurate tools to account for nonlinearity, and second, we propose a methodology for the elicitation of the nonlinear functions based on the analytic hierarchy process (AHP). This research creates a platform for further work on decision-making methodologies, and their implementation in the field of highway planning.

II. LITERATURE REVIEW

There are many approaches to decision making in the transportation context, as discussed extensively by Meyer and Miller [1]. The most structured approach, which is commonly used in environmental decision making, is termed as the "rational actor" approach. This approach aims to attain predetermined goals and objectives in a way that maximizes the utility based on a set of defined evaluation criteria. Operationalizing this approach to decision making is based on decision theory, which is an important field of study in operations research and management-oriented research.

The aims of the transportation planning processes, in our case a specific sustainability evaluation process, can be viewed as a multicriteria decision problem that needs to address a set of (often conflicting) objectives. As discussed by Bell and Keeney [2], the main characteristic of a multi-objective decision problem is the presence of multiple attributes which affect the decision. Some of these attributes may be intangible or expressed in incommensurable units. The final set of attributes selected need to be relevant, inclusive, non-overlapping, and operational. For the particular application discussed here, the performance measures (attributes) were developed in consultation with the transportation agency, and are listed in the following section.

Several basic references on MCDM describe general approaches to solve such decision problems. These include Keeney and Raiffa [3] and Von Winterfeldt and Edwards [4], where the multiattribute utility theory (MAUT)/simple multiattribute rating technique (SMART) approach is dealt with in detail. The basic methodology for these involves decomposing a

multiattribute utility function into an additive model that includes single-attribute utilities for each.

Their application of such models in the transportation planning field include the evaluation of sustainability of highway corridors by Zietsman *et al.* [5] using the MAUT and a similar approach to evaluate alternative transportation and land use scenarios for the Metro Atlanta region [6]. Leleur and Berg [7] proposed a comprehensive model for transportation project evaluation that combined the MAUT approach with a cost-benefit analysis. Other transportation sustainability evaluation efforts [8], [9], which are conducted at the global level also make use of utility–value functions to evaluate sustainability index scores based on relevant criteria.

The basic methodology common to all the studies cited above can be summarized by the following steps.

1) Selection of criteria and related attributes (performance measures) that reflect sustainability concerns.
2) Quantifying levels of the selected attributes, and scaling them to reflect relative preferences based on a "utility function" or "value function."
3) Measuring overall utility–value of different alternative scenarios based on the scaled values.
4) Obtain the final evaluation index value as the weighted sum of the attribute utilities–values.

This provides a clear method for converting qualitative attributes into quantitative measures, operating under the assumption of additive utilities. Such MAUT-based processes are still favored widely for a simple approach to decision-making problems, especially among agencies that do not have the knowledge/resources to dedicate to more advanced decision-making applications. As discussed by Fishburn [10], in such a model, a negative trend on one attribute can be compensated by improving another attribute. While such tradeoffs may be problematic, the proper choice of attributes, and structuring of the utility functions can counter this to a large extent [11].

A. Elicitation of Value Functions

In most transportation-related applications of the MAUT process, the scaling of the utility values (derivation of utility–value functions) is not investigated in great detail. It is performed by considering a linear variation from the "best" to "worst" values, or, as in the case of the study of Metro Atlanta [6]; values are scaled relative to the best-case scenario. This method of scaling utilities essentially makes a simplification/assumption that the utility of different alternatives varies linearly with a difference in performance measure value. While linear scaling may be sufficient for a majority of the performance measures, certain measures may benefit from nonlinear scaling.

Von Winterfeldt and Edwards [4] classified the methods of eliciting value functions in the SMART approach as the indifference methods and the numerical estimation methods. Yu [12] similarly classified the various methodologies of eliciting value functions into three main categories. The first involved the direct application of calculus, the second group of methods involved interactive methods (that are further described in Keeney

and Raiffa [3]), while the third included statistical/mathematical methodologies including Eigenvector type problems.

This third class of methods is similar to the approach discussed by Accorsi *et al.* [13] for the construction of utility functions for environmental decision making based on the AHP and linguistic fuzzy sets. The AHP is a technique most commonly used for criteria-weight elicitation in decision making [14], though it has a wide variety of applications and methods of implementation. The usefulness of the AHP is in its flexibility, which allows modification to a variety of situations that require subjective judgment translated into numerical quantities [15].

In this study, an approach based on the AHP is proposed for constructing selected value functions. The values are based on performance measure data collected for the test corridor, and projected extreme (best/worst case) values. The AHP matrices are constructed based on the relative importance of achieving different attribute scenarios. By linear algebra, the relative incremental utilities of various levels of the attributes were calculated, from which a utility function can be derived.

B. Utility–Value Distinction

The distinction between the utility and value within the decision-making framework is a fine one. Some authors have objected to the terms being used interchangeably, and the distinction between the two terms has been explored in detail in [3], [16]. Others, however, have stated that the value–utility distinction is spurious in the context of the MAUT/SMART type approach [4]. In general, however, the term "utility" comes into play when there is a risk associated with the outcomes, while the term "value" refers to riskless events.

The decision-making problem in this paper is considered not to have uncertainty associated with the outcomes or, better, the decision-making problem is assumed to have a deterministic nature, which is of course an approximation, but commonly adopted in practice, specifically, within the context of our case study. Therefore, it deals with "value" functions. However, for the remainder of this paper, the terms "value" and "utility" are used interchangeably and value–utility functions are referring to functions that translate the levels of a specific attribute into a scaled value representing the desirability of that level. These functions are used for the various attributes to obtain the final additive "index" value as the weighted sum.

III. MULTICRITERIA ANALYSIS FRAMEWORK

The overall research, in which the particular topic dealt by this paper fits into, has been discussed elsewhere in greater detail [17], [18]. The research goal was to develop and implement a tool that generates a "sustainability index" value for a highway, which can be estimated for current conditions, and for a future planning scenario. The methodology is designed to work for a given highway section, subdivided into smaller links. The case study corridor used in this paper was a 15-mi section of US Highway 281 in San Antonio, Texas. The results presented in this paper also pertain to this corridor. The study section had been subdivided into four links, and the sustainability index was estimated for each link, as well as for the total section for a base
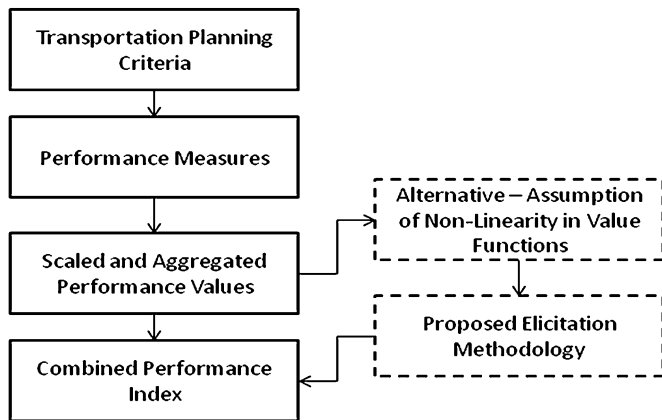
Fig. 1. Multicriteria analysis framework.

Fig. 2. Illustration of scaling for performance measures.

case scenario (representing conditions as of 2005), and a future case scenario (representing projected conditions for 2025). A set of performance measures were developed in consultation with key transportation agency personnel, who represented the decision makers. These performance measures were implemented in a MCDM problem along the lines of the MAUT/SMART approach. Fig. 1 provides a representation of the analysis framework. The portion of the figure with the dashed outline indicates the part of the overall research that is dealt with in this paper.

The MAUT process, as applied to derive the "sustainability index" value in our case study can be described in the following.

1) An estimation procedure was conducted for each of the performance measures, for which the best and worst case values (scaling extremes) were defined.
2) Each performance measure, once quantified, can then be expressed as scaled value on a 0–1 scale.
3) Each performance measure is assigned a weight through a standard weight-elicitation procedure conducted with the decision makers. The scaled utility values of individual measures are then aggregated together as a weighted sum to obtain the overall sustainability evaluation result.

A. Quantification and Scaling of Performance Measures

The details of the estimation of performance measures used in this study and their extreme values are discussed in [18]. Certain performance measures are already expressed as a percentage value, or on a 0–1 scale. In these cases, the measures represent the scaled value. For other performance measures, a value function must be constructed for scaling. The function expresses the variation in the scaled values over a range of quantified performance measure values. So, for each performance measure, there are two points that are fixed on the curve—the first corresponding to the best possible value of the performance measure (which would be assigned a scaled value = 1) and the second corresponding to the worst possible value of the performance measure (which would be assigned a scaled value = 0), as shown in Fig. 2. Therefore, the task of deriving a value function involves fitting a curve through these two fixed points. The most commonly assumed and simple value function is a straight line, which is referred to as "linear scaling". If any
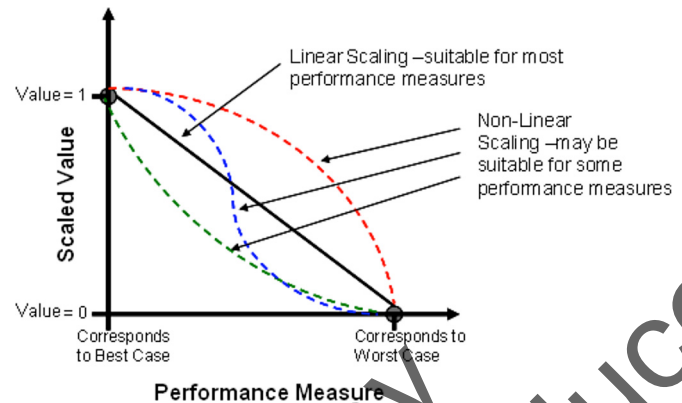
other shape or functional form is assumed, the scaling is deemed to be "nonlinear," as the figure illustrates. The use of linear or nonlinear utility functions in an MAUT analysis is a choice made by decision makers or those involved with structuring the decision problem. Often, linearity is assumed for simplicity. However, there is an underlying assumption while using linear scaling, which is the value of improving a performance measure is the same, no matter what the initial value of the performance measure is. However, for certain measures, it can be intuitively understood that improving the performance when it is close to the worst case scenario is more valuable than a similar improvement occurring closer to the best case scenario. For example, if we consider travel times for a specific roadway, the value of an initial travel time savings of 5 min may be of greater benefit than a subsequent savings of an additional 5 min. This will not be reflected in the linear function.

B. Nonlinear Utility Scaling Using the AHP

The issue of nonlinear utility scaling was addressed in a previous study of sustainable transportation performance measures [5], where different attributes were considered to have different shapes of utility functions. These functions, while being an improvement over assuming linearity, were defined based on mathematical properties of the function's shape.

In this research, linear scaling was considered as a default for all the performance measures, as it is generally assumed in practice. In addition, since the value functions should reflect a realistic representation of how the values of various performance measures are perceived by decision makers to impact highway sustainability, nonlinear value functions are elicited in order to compare the difference between using linear and nonlinear scaling. Table I summarizes the performance measures, their extreme values, and the type of scaling considered for each measure. Of these, two of the measures (shown in italics) have been selected to illustrate the process for obtaining nonlinear value functions. All performance measures are evaluated for the existing conditions, as well as for a projected future scenario for the case study corridor. Based on the data elements, the performance measures can be quantified for individual links

TABLE I
DETAILS OF EXTREME VALUES AND TYPES OF SCALING FOR ALL MEASURES

Reference Number	Performance Measure	Extreme Values		Type of Scaling
		Best	Worst	
1a	Travel Time Index	1.00	1.50	Linear scaling of values
1b	Buffer Index	0.00	0.65	Linear scaling of values
2a	Annual severe crashes per mile	Depends on roadway type and number of lanes		Linear scaling of values
2b	Percentage lane miles under TMC surveillance	100%	0%	Measure represents value
3a	Land-use balance	1.00	0.00	Measure represents value
3b	Truck Throughput Efficiency	170,704 daily truck miles/hour	5,640 daily truck miles/hour	Linear scaling of values
4a	Pavement condition score	100	0	Measure represents value
4b	Capacity addition within ROW	1.00	0.00	Measure represents value
4c	Cost recovery from alternate sources	1.00	0.00	Measure represents value
4d	*Proportion of total person-miles of travel on non-SOVs*	*77%*	*25%*	*Non-linear scaling of values*
5a	*Daily NO$_x$, CO, and VOC emissions*	*1.28 kilograms per mile*	*180.5 kilograms per mile*	*Non-linear scaling of values*
5b	Daily CO$_2$ emissions	2,993 kilograms per mile	92,702 kilograms per mile	Linear scaling of *values*
5c	Attainment of ambient air quality standards	1.00	0.00	Measure represents value

(that the study section is subdivided into), and for the overall study section also.

While the process described in this paper is completely in line with a traditional MAUT/SMART model, authors chose to use an elicitation procedure to obtain single attribute value functions, instead of the direct rating, as generally done in SMART [4]. The choice of AHP as elicitation method for the two selected performance measures was made during the study design process and driven by the preference of the decision makers participating in the case study, some of whom were familiar with and biased toward the AHP. While AHP is not as simple as direct rating to obtain values, it is still designed to obtain a single set of inputs from each decision maker for use in deriving the functions, and it places a lesser burden on the decision maker when compared with other interactive elicitation methods, which involve greater level of interaction/questioning with the decision maker (as discussed in Keeney and Raiffa [3], and Yu [12]), and it was found to be easily implemented in practice. Our case study compares two corridor options, but the methodology could be widely applicable for a variety of highway corridor decision-making contexts and be used to generate scaled values for the performance measures under various analysis scenarios.

The AHP is a process of eliciting the relative importance of different scenarios or quantities by making pair-wise comparisons between them. While it is usually employed for elicitation of weights used to rank the importance of criteria, in this research, it is used to compare the relative desirability of obtaining different levels of incremental improvement over the range of possible performance measure values. Based on the results of the comparisons made, an AHP matrix can be constructed, from which the relative desirability of different levels of the performance measure, and consequently, data points on the value-curve can be obtained. The AHP decision-making process was performed through a guided workshop for a group of decision makers, namely six transportation agency officials and transportation planners, who had a sound knowledge and understanding of the planning process and of the particular performance measures being discussed. Usually, an AHP procedure can use either a single set of responses obtained through consensus from the group of decision makers or an average of the responses [13]. For this process, the individual responses were collected from each decision maker, with a view of examining the trends and similarities between them, and later translated to a single set of responses to derive the value function.

The two selected performance measures are indicated in Table I and represented those that were easily understood by the group of decision makers, and for which the application of nonlinear utility scaling made the most sense. The first measure selected, quantifies the daily emissions of the oxides of nitrogen (NO$_x$), carbon monoxide (CO), and volatile organic compounds (VOC). The other measure quantifies the proportion of total person-miles of travel that is in a non single occupant vehicle (SOV). For the emissions measure, it is generally accepted that the benefits of reducing emissions at the "worse" end of the spectrum should be given greater importance. It was felt that the input of decision makers in assessing how the value of the measure varies would be useful. Similarly, for the measure considering SOV travel—it is well known that in the United States, a majority of transportation occurs as SOV (automobile) travel. Thus, it was felt that it was appropriate to introduce nonlinear scaling to reflect the decision makers' perspective on how best the credit increases in non single-occupant travel. The process of deriving the utility function is described in detail for the emissions measure, while only the results are presented for the measure concerning non-SOV travel.

C. Derivation of Value Function for Daily NO$_x$, CO, and VOC Emissions

This performance measure quantifies the total daily emissions of NO$_x$, CO, and VOC due to automobile emissions per mile of roadway. It is expressed as grams per mile, and the combined measure is arrived at by weighting the emissions of each pollutant according to their respective pollutant damage costs. The scaling extremes, i.e., the projected best case scenario and worst case scenario for this particular measure correspond to the combined emission levels of 1.28 and 180.5 kg/mi, respectively. Based on this knowledge, two points on the curve can be fixed, as shown in Fig. 3.
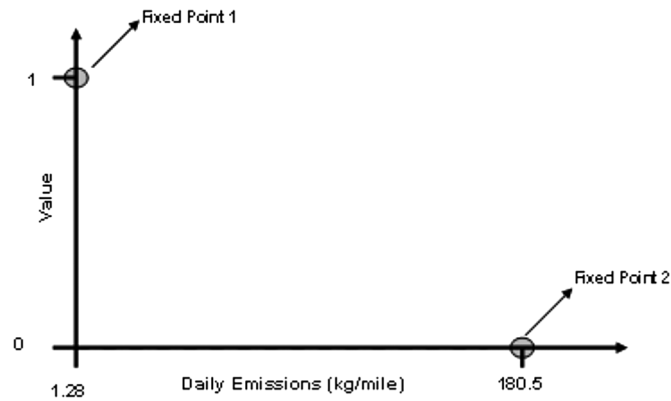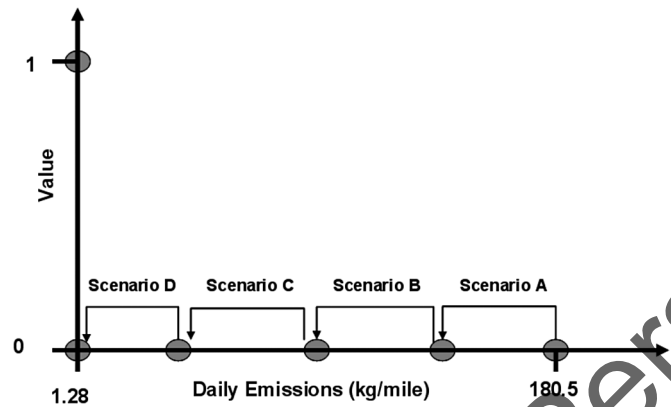
Fig. 3. Fixed points on value-curve for emissions.

Fig. 4. Scenarios defined for the emission performance measures.

To derive a value function between these two points, the range of values on the x-axis is split into four increments. The case of reducing emissions at each increment is termed as a scenario. For example, Scenario X could be defined as reducing daily emissions from 181 to 125 kg/mi, while Scenario Y could be defined as reducing emissions from 125 to 100 kg/mi. Based on knowledge of the performance measure and its variation, it is possible to compare the relative desirability or importance of the scenarios. This strength of preference is expressed on a numerical scale 1–9, using a set of guidelines as devised by Saaty [14]. A score of 1 implies that both scenarios are equally important, and a score of 9 implies that one scenario is absolutely more important than the other. Pair-wise comparisons are made for each pair of defined scenarios, and the results are used to populate an AHP matrix, from which the weights for each of the scenarios (totaling to 1) can be obtained. Since the utility values are also on a 0–1 scale, the weights for each scenario thus represent their incremental value, from which the value curve can be derived. The AHP matrix can also be used to check for consistency in a set of responses, and to rectify any inconsistencies in the decision-making process.

For the emission measures, four scenarios are defined covering the range of possible emission levels between the best and worst case projections (see Fig. 4).

Table II provides the numerical details of each scenario. Verbal descriptors were used (ranging from "very bad," "bad,"

TABLE II
EVALUATION SCENARIOS FOR EMISSION MEASURES

| Scenario | Description of Improvement | |
	Daily Emissions	Verbal Descriptor*
A	180.50 kg/mile to 135.70 kg/mile	Very Bad to Bad
B	135.70 kg/mile to 90.89 kg/mile	Bad to Moderate
C	90.89 kg/mile to 46.09 kg/mile	Moderate to Good
D	46.09 kg/mile to 1.28 kg/mile	Good to Very Good

*The verbal descriptors were further described to the decision maker in technical terms, specific to the performance measure in question.

TABLE III
AHP MATRIX FOR DERIVING UTILITIES

Scenario	A	B	C	D
A	1.00	5.00	7.00	9.00
B	0.20	1.00	5.00	7.00
C	0.14	0.14	1.00	3.00
D	0.11	0.20	0.14	1.00

"moderate," "good," and "very good") to describe the levels of attainment for each scenario. The verbal descriptors were further described to the decision makers specific to the performance measure in question. For example, for the emission measures, the "very bad" scenario represented the kind of emissions associated with heavy, highly congested traffic, while the "very good" scenario was represented by emissions associated with free flowing, lower volume traffic conditions. Intermediate scenarios were also similarly described in a manner that the decision makers were able to understand. Decision makers were asked to perform a total of six pair-wise comparisons on the AHP scale, for all possible combinations of the scenarios. Based on the responses, an AHP matrix can be compiled and used to calculate points on the curve, and checked for consistency.

Rather than providing decision makers with scenarios related to actual levels of the performance measurement, an alternative approach could have been adopted to relate the performance measure (in this case, emissions) to the cost of impacts (such as health, environmental damage). However, the AHP process proposed is based on deriving the decision makers' perception of how the value of a measure varies as the measure itself varies. Given this, it was felt that consideration of the measure rather than the costs was preferable, because decision makers may tend to judge quantities expressed as costs having a linear variation of utility.

1) Construction of AHP Matrix and Derivation of Values:
The AHP matrix is a square matrix of order equal to the total number of options evaluated (in this case, four scenarios). The rows and columns represent each scenario, and each cell of the matrix represents the degree to which the row component dominates the column component on the AHP scale. If the column component is the dominant option, the reciprocal of the AHP scale score is entered as the cell value instead. The diagonal values of the AHP matrix are always unity, as each element is equally important when compared to itself ($= 1$ on the AHP scale). Table III shows the AHP matrix used to derive the value

TABLE IV
NORMALIZED EIGENVECTOR FOR RELATIVE PRIORITIES

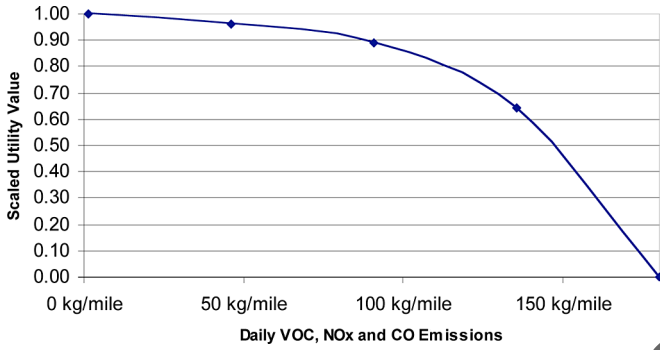| Scenario	Relative Priority (Eigen Vector)	Cumulative Priority (Utility Curve)
A	0.64	0.64
B	0.25	0.88
C	0.08	0.97
D	0.04	1.00

Fig. 5. Value function plotted from results of AHP evaluation- emission measures.

function, and is based on the responses from the six individual decision makers.

For this matrix, the normalized Eigenvector represents the relative desirability of the different scenarios (each of which represents a specific increment in the performance measure value). Thus, the location of various points on the curve can be determined, from which a function can be derived. Table IV shows the calculated values used to identify points on the curve, and Fig. 5 shows the shape of the value function derived.

2) Checking for Consistency: The consistency of responses obtained from the AHP can be checked by calculating the consistency index (CI) and consistency ratio (CR), as shown in (1) and (2), respectively. Generally, CR values below 0.1 indicate a good degree of consistency in the pair-wise comparisons. The CI and CR values for this measure are 0.09 and 0.1, respectively, which are found to be satisfactory.

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{1}$$

$$CR = \frac{CI}{RI} \tag{2}$$

where

n = order of matrix;
$\lambda_{\max}$ = principal Eigenvalue of AHP matrix;
RI = random index -0.9 for matrix of order 4.

3) Deriving Equation for Value Function Based on AHP Results: Based on the data points obtained from the AHP, a value function is derived using a method of least squares estimation
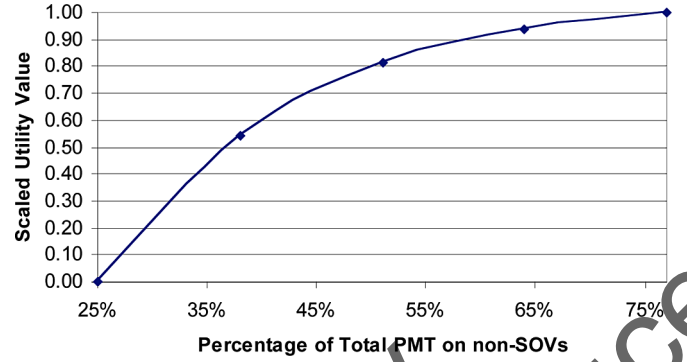

Fig. 6. Value function based on results of AHP evaluation- non-SOV travel measure.

(see (3)).

$$y = 1.019 - 0.018e^{0.022x} \tag{3}$$

where

y = scaled value;
x = combined VOC, NO$_x$, and CO emissions, in kg/mi.

D. Derivation of Value Function for Proportion of Non-SOV Travel

This performance measure quantifies the proportion of total daily person miles of travel that occurs in a non-SOV (this includes higher automobile occupancies, as well as bus and rail transit). The best and worst case scenarios for this measure are defined based on attaining overall equivalent automobile occupancy levels of 1.63 and 1.14 corresponding to figures from the latest *National Household Travel Survey* [19]. These values translate the performance measure values of 77% and 25% as the best and worst cases, respectively. The value function for this measure is derived using the same technique as for the previous measure. Fig. 6 shows the curve for this measure. The CI and CR values were 0.066 and 0.073, respectively, indicating a fairly high level of consistency.

Equation (4) shows the value function derived for this performance measure.

$$y = 1.059 - 4.249e^{-5.558x} \tag{4}$$

where

y = scaled value;
x = percentage of total person miles of travel that is in a non-SOV.

E. Summary of the Scaling Process

The process of scaling of various performance measures was discussed in this section. Some of the performance measures (expressed as a percentage, or on a 0–1 scale) already reflected their scaled values. For other measures, linear scaling was considered for the majority, while a methodology for deriving nonlinear value functions for scaling was proposed, and demonstrated for two selected measures.

TABLE V
COMPARISON OF SCALED VALUES FOR MEASURES AND AGGREGATE INDEX

Comparison for Emissions Measure

Link	Base Case Scenario				Future Case Scenario			
	Scaled Value for Measure		Percentage Change over Linear	Absolute Difference	Scaled Value for Measure		Percentage Change over Linear	Absolute Difference
	Non Linear Value Curve	Linear Value Curve			Non Linear Value Curve	Linear Value Curve		
1	0.68	0.13	423%	0.55	0.97	0.73	33%	0.24
2	0.77	0.22	250%	0.55	0.97	0.7	38%	0.27
3	0.96	0.63	52%	0.33	0.98	0.82	20%	0.16
4	0.96	0.67	43%	0.29	0.99	0.87	14%	0.12
Total Section	0.86	0.36	139%	0.5	0.98	0.76	29%	0.22

Comparison for Non-SOV Measure

Link	Base Case Scenario				Future Case Scenario			
	Scaled Value for Measure		Percentage Change over Linear	Absolute Difference	Scaled Value for Measure		Percentage Change over Linear	Absolute Difference
	Non Linear Value Curve	Linear Value Curve			Non Linear Value Curve	Linear Value Curve		
1	0.6	0.29	107%	0.31	0.6	0.29	107%	0.31
2	0.6	0.29	107%	0.31	0.6	0.29	107%	0.31
3	0.6	0.29	107%	0.31	0.6	0.29	107%	0.31
4	0.6	0.29	107%	0.31	0.6	0.29	107%	0.31
Total Section	0.6	0.29	107%	0.31	0.6	0.29	107%	0.31

Comparison for Aggregate Index Value

Link	Base Case Scenario				Future Case Scenario			
	Index Value		Percentage Change over Linear	Absolute Difference	Index Value		Percentage Change over Linear	Absolute Difference
	With Non Linear Value Curves	All Linear Value Curves			With Non Linear ValueCurves	All Linear Value Curves		
1	0.54	0.43	26%	0.11	0.38	0.33	15%	0.05
2	0.65	0.54	20%	0.11	0.36	0.3	20%	0.06
3	0.58	0.51	14%	0.07	0.55	0.51	8%	0.04
4	0.57	0.51	12%	0.06	0.65	0.63	3%	0.02
Total Section	0.6	0.5	20%	0.1	0.41	0.36	14%	0.05

IV. RESULTS AND DISCUSSION

To assess the impact of using the derived nonlinear utility functions instead of assuming linear utility functions for the selected performance measures, two comparisons were performed and discussed in the following sections.

A. *Comparison of the Difference in Scaled Values for the Individual Measures*

A comparison between the scaled values for the emissions performance measure using the value function that was derived, and assuming a linear variation, is presented in Table V. The comparisons are shown for both the base and the future cases, and for the entire case study corridor, as well as in the corresponding sections. For this measure, it was seen that the scaled value using the derived functions varied from the linear assumption by a magnitude ranging from 14% to 423%. The range of variation can be attributed to the variations of the quantified measure between the base and the future cases, and among various roadway segments. There was less variation that could be inferred from the measure relating to the proportion of non-SOV travel, as the quantified performance measure was the same for all links on the section, for both the base and the future cases, respectively. However, there was a 107% increase in the scaled measure value, when the nonlinear utility function was used instead of a linear utility function.

B. Comparison of the Difference in the Total Index Value

The aggregate index value is calculated as the weighted sum of the individual scaled measures. The set of 13 measures applied to the study corridor are assigned individual weights (adding to 1), thus, the aggregate index value is also expressed on a 0–1 scale. The index value is calculated for the case study, considering the nonlinear scaling for the two measures, and is compared with the index value calculated by assuming linear utility functions for the two measures also. The findings are also shown in Table V. It is seen that the index values are impacted ranging from a magnitude of 3% to 26%. This represents degrees of varying impact on the final results, and is a lesser range of values when compared to those from individual measures. However, it is still observed that the consideration of nonlinear scaling for even a small subset of measures can affect the outcome of the overall MCDM analysis.

V. Observations and Conclusion

It can be seen that taking into account the nonlinearity of utility can significantly impact the results in terms of the scaled value for a quantified measure. The aggregated sustainability index is made up of a set of performance measures, most of which are scaled using linear utility functions. However, the derivation and assumption of nonlinear utility functions, even for just two performance measures out of a total of thirteen is found to impact the final aggregate index value in most cases. It is fairly obvious that the nature and the magnitude of the impact depend upon the values of the individual measures quantified for a particular case. Another factor that can affect the result is the weights assigned to the different measures. It can still be concluded, however, that the use of nonlinear utility functions for performance measures in the MAUT analysis can significantly impact the results and findings.

In summary, the following are indicated from the findings in this paper.

1) While the MAUT provides a suitable decision-making methodology for transportation planning applications, it is indicated that the results from an MAUT analysis can be significantly impacted by how the scaling is performed for individual performance measures.

2) The extent of the difference between linear and nonlinear scaling for a performance measure is dependent upon the value of the performance measure itself (i.e., where it lies on the value curve). This indicates that the construction of value functions needs to be given importance.

3) The proposed AHP-based methodology requires a single questionnaire input from the decision makers to elicit value functions, which provides a useful alternative to direct rating and other approaches that sometimes require "back and forth" interaction to construct a function.

4) However, given the extent to which input from the decision makers plays a role in this process (from the selection of performance measures, to assigning weights, and providing input for the construction of functions), it is necessary that the decision makers are objective and do not introduce any bias. The authors posit that providing the

questionnaires and formalizing the decision-making process helps preventing bias to a certain extent, as it allows the decision makers to consider their thought processes instead of relying solely on intuitive judgments.

A. Limitations and Scope for Further Research

Careful consideration of the utility variations assumed in a performance measurement-based analysis needs to be warranted. In this respect, the AHP-based procedure proposed in this paper provides a possible methodology for assessing the value functions. This methodology allows certain performance measures to be scaled according to how the decision makers' values improve a measure, relative to their own assessment of the measure's value. Although the AHP process might be considered as an unconventional tool to be used in this context and is controversial among some researchers in the MCDM field, it was found to be fairly straightforward to implement and we are fairly confident that results (linearity versus nonlinearity comparison) would not change much by using alternative elicitation methods. It would be interesting to see a comparison between alternative techniques and further research into the assessment of value and utility functions, specifically developed for transportation planning applications. This would prove useful to improve how MCDMmethodologies are approached in transportation sector. Also, the results and findings were compared only for a single case study corridor. The expansion to include other cases will also serve to further strengthen this research.

References

[1] M. Meyer and E. Miller, *Urban Transportation Planning: A Decision Oriented Approach*. New York: McGraw-Hill Higher Education, 2001.

[2] D. Bell, R. L. Keeney, and H. Raiffa, *Conflicting Objectives in Decisions*. New York: Wiley, 1977.

[3] R. L. Keeney and H. Raiffa, *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*. New York: Wiley, 1976.

[4] D. Von Winterfeldt and W. Edwards, *Decision Analysis and Behavioral Research*. New York: Cambridge Univ. Press, 1986.

[5] J. Zietsman, L.R. Rilett, and S. Kim, "Transportation corridor decision making with multi-attribute utility theory," *Spec. Issue Int. J. Manage. Decision Making*, vol. 7, no. 2/3, pp. 255–266, 2006.

[6] C. Jeon, A. Amekudzi, and R. Guensler, "Sustainability assessment at the transportation planning level: performance measures and indexes," presented at the 87th Annu. Meet. Transp. Res. Board, Washington, DC, 2008.

[7] S. Leleur and N. Berg, "The COSIMA approach to transport decision making: combining cost-benefit and multi-criteria analysis for comprehensive project appraisal," presented at the Korean Dev. Inst. World Bank Conf., Seoul, South Korea, 2007.

[8] W.R. Black, "Toward a measure of transport sustainability," presented at the 79th Annu. Meet. Transp. Res. Board, Washington, DC, 2000.

[9] Yale University. (2005) *2005 Environmental Sustainability Index: Benchmarking national environmental stewardship*. New Haven, CT: Yale Center for Environmental Law and Policy, Yale University, [Online]. Available: http://www.yale.edu/esi/ESI2005_Main_Report.pdf

[10] P. C. Fishburn, *Utility Theory for Decision Making*. New York: Wiley, 1970.

[11] E. Triantaphyllou, *Multi-Criteria Decision Making Methods: A Comparative Study*. The Netherlands: Kluwer, 2001.

[12] P. Yu, *Multiple Criteria Decision Making: Concepts, Techniques and Extensions*. New York: Plenum, 1985.

[13] R. Accorsi, E. Zio, and G. E. Apostolakis, "Developing utility functions for environmental decision making," *Prog. Nucl. Energy*, vol. 34, no. 4, pp. 387–411, 1999.

[14] T. L. Saaty, *The Analytic Hierarchy Process*. New York: McGraw-Hill International, 1980.

[15] T. L. Saaty and L. G. Vargas, *Models, Methods, Concepts and Applications of the Analytic Hierarchy Process*. Norwell, MA: Kluwer, 2001.

[16] K. Fischer. (2005). *Value Functions versus Utility Functions*. Birmingham, UK: Aston University, [Online]. Available: http://www.abs.aston.ac.uk/newweb/research/publications/docs/RP0416.pdf

[17] J. Zietsman, W. Knowles, T. Ramani, B. Bochner, and J. Lee, "Sustainability enhancement tool for state DOTs using performance measurement," presented at the 87th Annu. Meet. Transp. Res. Board, Washington, DC, 2008.

[18] T. Ramani, "An improved methodology for multi-criteria assessments of highway sustainablity," M.S. Thesis, Texas A&M Univ., College Station, Texas, 2008.

[19] P. Hu, and T. R. Reuscher. (2004, Dec.). *Summary of Travel Trends: 2001 National Household Travel Survey*. [Online]. Available: http://nhts.ornl.gov/2001/pub/STT.pdf

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Accounting for Nonlinearity in the MCDM Approach for a Transportation Planning Application

Tara L. Ramani, Luca Quadrifoglio, and Josias Zietsman

Abstract—We assess the impact of accounting for nonlinearity of selected value functions to improve the multiattribute utility theory approach for transportation planning applications. Research findings were obtained by conducting a case study for investigating and improving the project evaluation and selection with the collaboration of a state-level transportation agency. A methodology based on the analytic hierarchy process has been used for elicitation of the nonlinear value functions. It was found that employing nonlinear functions, as opposed to the commonly assumed linear scaling, even for only a subset of performance measures, had a significant impact in calculating the projects' index final scores, with changes ranging from 3% to 26%, possibly overturning the project selection. This paper highlights the importance that needs to be given to construct the value functions in decision-making problems and shows how the process could be improved by employing available tools properly.

Index Terms—Analytic hierarchy process, multiattribute utility theory (MAUT), multicriteria decision making (MCDM), value functions.

I. INTRODUCTION

TRANSPORTATION planning has always been characterized by the presence of an institutional framework that guides the planning process. There are also a variety of factors, such as political concerns, funding availability, agency jurisdiction, socio-economic and environmental issues, which act as constraints to transportation decision making. While historically, a majority of transportation decision making did not follow a formalized process, there has been a shift in recent times to apply performance measurement and decision-making processes.

Framing a transportation-planning problem using a multicriteria decision-making (MCDM) approach (with the aim of satisfying a set of objectives) is a reasonable way of addressing all the associated constraints and concerns. The ultimate aim of implementing a decision-making process is to allow the evaluation of alternatives on a common basis and enable sound decisions regarding future courses of action. This paper deals with such a decision-making methodology developed for a state-level transportation agency.

The topic of this paper fits within an overall research context involving the development of a user-friendly tool that incorporated sustainability concerns into the transportation planning process, with the use of performance measures that were evaluated to generate a "sustainability index" or "project index" value for use in decision making. The tool is currently being implemented into transportation planning practice by a state-level transportation agency.

Specifically, this paper highlights an aspect of the decision-making process, which is generally well known and understood theoretically, but often overlooked in practice and in particular, by transportation planning agencies; i.e., decisions are often taken assuming linear models. This paper presents a case study, in which first, the error due to nonlinearity is quantified to emphasize the importance of the use of more accurate tools to account for nonlinearity, and second, we propose a methodology for the elicitation of the nonlinear functions based on the analytic hierarchy process (AHP). This research creates a platform for further work on decision-making methodologies, and their implementation in the field of highway planning.

II. LITERATURE REVIEW

There are many approaches to decision making in the transportation context, as discussed extensively by Meyer and Miller [1]. The most structured approach, which is commonly used in environmental decision making, is termed as the "rational actor" approach. This approach aims to attain predetermined goals and objectives in a way that maximizes the utility based on a set of defined evaluation criteria. Operationalizing this approach to decision making is based on decision theory, which is an important field of study in operations research and management-oriented research.

The aims of the transportation planning processes, in our case a specific sustainability evaluation process, can be viewed as a multicriteria decision problem that needs to address a set of (often conflicting) objectives. As discussed by Bell and Keeney [2], the main characteristic of a multi-objective decision problem is the presence of multiple attributes which affect the decision. Some of these attributes may be intangible or expressed in incommensurable units. The final set of attributes selected need to be relevant, inclusive, non-overlapping, and operational. For the particular application discussed here, the performance measures (attributes) were developed in consultation with the transportation agency, and are listed in the following section.

Several basic references on MCDM describe general approaches to solve such decision problems. These include Keeney and Raiffa [3] and Von Winterfeldt and Edwards [4], where the multiattribute utility theory (MAUT)/simple multiattribute rating technique (SMART) approach is dealt with in detail. The basic methodology for these involves decomposing a

multiattribute utility function into an additive model that includes single-attribute utilities for each.

Their application of such models in the transportation planning field include the evaluation of sustainability of highway corridors by Zietsman *et al.* [5] using the MAUT and a similar approach to evaluate alternative transportation and land use scenarios for the Metro Atlanta region [6]. Leleur and Berg [7] proposed a comprehensive model for transportation project evaluation that combined the MAUT approach with a cost-benefit analysis. Other transportation sustainability evaluation efforts [8], [9], which are conducted at the global level also make use of utility–value functions to evaluate sustainability index scores based on relevant criteria.

The basic methodology common to all the studies cited above can be summarized by the following steps.

1) Selection of criteria and related attributes (performance measures) that reflect sustainability concerns.
2) Quantifying levels of the selected attributes, and scaling them to reflect relative preferences based on a "utility function" or "value function."
3) Measuring overall utility–value of different alternative scenarios based on the scaled values.
4) Obtain the final evaluation index value as the weighted sum of the attribute utilities–values.

This provides a clear method for converting qualitative attributes into quantitative measures, operating under the assumption of additive utilities. Such MAUT-based processes are still favored widely for a simple approach to decision-making problems, especially among agencies that do not have the knowledge/resources to dedicate to more advanced decision-making applications. As discussed by Fishburn [10], in such a model, a negative trend on one attribute can be compensated by improving another attribute. While such tradeoffs may be problematic, the proper choice of attributes, and structuring of the utility functions can counter this to a large extent [11].

A. Elicitation of Value Functions

In most transportation-related applications of the MAUT process, the scaling of the utility values (derivation of utility–value functions) is not investigated in great detail. It is performed by considering a linear variation from the "best" to "worst" values, or, as in the case of the study of Metro Atlanta [6]; values are scaled relative to the best-case scenario. This method of scaling utilities essentially makes a simplification/assumption that the utility of different alternatives varies linearly with a difference in performance measure value. While linear scaling may be sufficient for a majority of the performance measures, certain measures may benefit from nonlinear scaling.

Von Winterfeldt and Edwards [4] classified the methods of eliciting value functions in the SMART approach as the indifference methods and the numerical estimation methods. Yu [12] similarly classified the various methodologies of eliciting value functions into three main categories. The first involved the direct application of calculus, the second group of methods involved interactive methods (that are further described in Keeney

and Raiffa [3]), while the third included statistical/mathematical methodologies including Eigenvector type problems.

This third class of methods is similar to the approach discussed by Accorsi *et al.* [13] for the construction of utility functions for environmental decision making based on the AHP and linguistic fuzzy sets. The AHP is a technique most commonly used for criteria-weight elicitation in decision making [14], though it has a wide variety of applications and methods of implementation. The usefulness of the AHP is in its flexibility, which allows modification to a variety of situations that require subjective judgment translated into numerical quantities [15].

In this study, an approach based on the AHP is proposed for constructing selected value functions. The values are based on performance measure data collected for the test corridor, and projected extreme (best/worst case) values. The AHP matrices are constructed based on the relative importance of achieving different attribute scenarios. By linear algebra, the relative incremental utilities of various levels of the attributes were calculated, from which a utility function can be derived.

B. Utility–Value Distinction

The distinction between the utility and value within the decision-making framework is a fine one. Some authors have objected to the terms being used interchangeably, and the distinction between the two terms has been explored in detail in [3], [16]. Others, however, have stated that the value–utility distinction is spurious in the context of the MAUT/SMART type approach [4]. In general, however, the term "utility" comes into play when there is a risk associated with the outcomes, while the term "value" refers to riskless events.

The decision-making problem in this paper is considered not to have uncertainty associated with the outcomes or, better, the decision-making problem is assumed to have a deterministic nature, which is of course an approximation, but commonly adopted in practice, specifically, within the context of our case study. Therefore, it deals with "value" functions. However, for the remainder of this paper, the terms "value" and "utility" are used interchangeably and value–utility functions are referring to functions that translate the levels of a specific attribute into a scaled value representing the desirability of that level. These functions are used for the various attributes to obtain the final additive "index" value as the weighted sum.

III. MULTICRITERIA ANALYSIS FRAMEWORK

The overall research, in which the particular topic dealt by this paper fits into, has been discussed elsewhere in greater detail [17], [18]. The research goal was to develop and implement a tool that generates a "sustainability index" value for a highway, which can be estimated for current conditions, and for a future planning scenario. The methodology is designed to work for a given highway section, subdivided into smaller links. The case study corridor used in this paper was a 15-mi section of US Highway 281 in San Antonio, Texas. The results presented in this paper also pertain to this corridor. The study section had been subdivided into four links, and the sustainability index was estimated for each link, as well as for the total section for a base
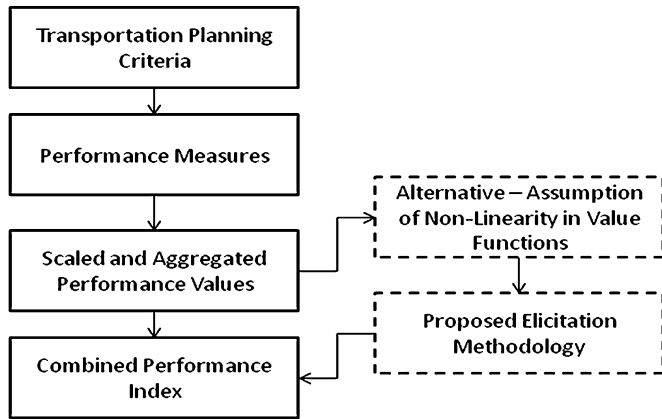
Fig. 1.   Multicriteria analysis framework.

Fig. 2.   Illustration of scaling for performance measures.

case scenario (representing conditions as of 2005), and a future case scenario (representing projected conditions for 2025). A set of performance measures were developed in consultation with key transportation agency personnel, who represented the decision makers. These performance measures were implemented in a MCDM problem along the lines of the MAUT/SMART approach. Fig. 1 provides a representation of the analysis framework. The portion of the figure with the dashed outline indicates the part of the overall research that is dealt with in this paper.

The MAUT process, as applied to derive the "sustainability index" value in our case study can be described in the following.

1) An estimation procedure was conducted for each of the performance measures, for which the best and worst case values (scaling extremes) were defined.
2) Each performance measure, once quantified, can then be expressed as scaled value on a 0–1 scale.
3) Each performance measure is assigned a weight through a standard weight-elicitation procedure conducted with the decision makers. The scaled utility values of individual measures are then aggregated together as a weighted sum to obtain the overall sustainability evaluation result.

A. Quantification and Scaling of Performance Measures

The details of the estimation of performance measures used in this study and their extreme values are discussed in [18]. Certain performance measures are already expressed as a percentage value, or on a 0–1 scale. In these cases, the measures represent the scaled value. For other performance measures, a value function must be constructed for scaling. The function expresses the variation in the scaled values over a range of quantified performance measure values. So, for each performance measure, there are two points that are fixed on the curve—the first corresponding to the best possible value of the performance measure (which would be assigned a scaled value = 1) and the second corresponding to the worst possible value of the performance measure (which would be assigned a scaled value = 0), as shown in Fig. 2. Therefore, the task of deriving a value function involves fitting a curve through these two fixed points. The most commonly assumed and simple value function is a straight line, which is referred to as "linear scaling". If any
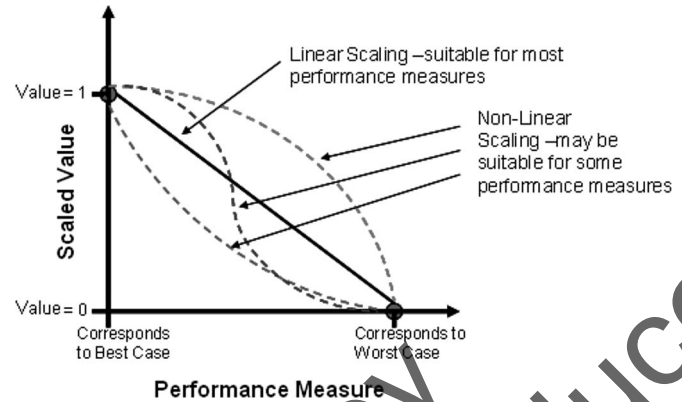
other shape or functional form is assumed, the scaling is deemed to be "nonlinear," as the figure illustrates. The use of linear or nonlinear utility functions in an MAUT analysis is a choice made by decision makers or those involved with structuring the decision problem. Often, linearity is assumed for simplicity. However, there is an underlying assumption while using linear scaling, which is the value of improving a performance measure is the same, no matter what the initial value of the performance measure is. However, for certain measures, it can be intuitively understood that improving the performance when it is close to the worst case scenario is more valuable than a similar improvement occurring closer to the best case scenario. For example, if we consider travel times for a specific roadway, the value of an initial travel time savings of 5 min may be of greater benefit than a subsequent savings of an additional 5 min. This will not be reflected in the linear function.

B. Nonlinear Utility Scaling Using the AHP

The issue of nonlinear utility scaling was addressed in a previous study of sustainable transportation performance measures [5], where different attributes were considered to have different shapes of utility functions. These functions, while being an improvement over assuming linearity, were defined based on mathematical properties of the function's shape.

In this research, linear scaling was considered as a default for all the performance measures, as it is generally assumed in practice. In addition, since the value functions should reflect a realistic representation of how the values of various performance measures are perceived by decision makers to impact highway sustainability, nonlinear value functions are elicited in order to compare the difference between using linear and nonlinear scaling. Table I summarizes the performance measures, their extreme values, and the type of scaling considered for each measure. Of these, two of the measures (shown in italics) have been selected to illustrate the process for obtaining nonlinear value functions. All performance measures are evaluated for the existing conditions, as well as for a projected future scenario for the case study corridor. Based on the data elements, the performance measures can be quantified for individual links

TABLE I
DETAILS OF EXTREME VALUES AND TYPES OF SCALING FOR ALL MEASURES

Reference Number	Performance Measure	Extreme Values		Type of Scaling
		Best	Worst	
1a	Travel Time Index	1.00	1.50	Linear scaling of values
1b	Buffer Index	0.00	0.65	Linear scaling of values
2a	Annual severe crashes per mile	Depends on roadway type and number of lanes		Linear scaling of values
2b	Percentage lane miles under TMC surveillance	100%	0%	Measure represents value
3a	Land-use balance	1.00	0.00	Measure represents value
3b	Truck Throughput Efficiency	170,704 daily truck miles/hour	5,640 daily truck miles/hour	Linear scaling of values
4a	Pavement condition score	100	0	Measure represents value
4b	Capacity addition within ROW	1.00	0.00	Measure represents value
4c	Cost recovery from alternate sources	1.00	0.00	Measure represents value
4d	*Proportion of total person-miles of travel on non-SOVs*	*77%*	*25%*	*Non-linear scaling of values*
5a	*Daily NO_x, CO, and VOC emissions*	*1.28 kilograms per mile*	*180.5 kilograms per mile*	*Non-linear scaling of values*
5b	Daily CO_2 emissions	2,993 kilograms per mile	92,702 kilograms per mile	Linear scaling of values
5c	Attainment of ambient air quality standards	1.00	0.00	Measure represents value

(that the study section is subdivided into), and for the overall study section also.

While the process described in this paper is completely in line with a traditional MAUT/SMART model, authors chose to use an elicitation procedure to obtain single attribute value functions, instead of the direct rating, as generally done in SMART [4]. The choice of AHP as elicitation method for the two selected performance measures was made during the study design process and driven by the preference of the decision makers participating in the case study, some of whom were familiar with and biased toward the AHP. While AHP is not as simple as direct rating to obtain values, it is still designed to obtain a single set of inputs from each decision maker for use in deriving the functions, and it places a lesser burden on the decision maker when compared with other interactive elicitation methods, which involve greater level of interaction/questioning with the decision maker (as discussed in Keeney and Raiffa [3], and Yu [12]), and it was found to be easily implemented in practice. Our case study compares two corridor options, but the methodology could be widely applicable for a variety of highway corridor decision-making contexts and be used to generate scaled values for the performance measures under various analysis scenarios.

The AHP is a process of eliciting the relative importance of different scenarios or quantities by making pair-wise comparisons between them. While it is usually employed for elicitation of weights used to rank the importance of criteria, in this research, it is used to compare the relative desirability of obtaining different levels of incremental improvement over the range of possible performance measure values. Based on the results of the comparisons made, an AHP matrix can be constructed, from which the relative desirability of different levels of the performance measure, and consequently, data points on the value-curve can be obtained. The AHP decision-making process was performed through a guided workshop for a group of decision makers, namely six transportation agency officials and transportation planners, who had a sound knowledge and understanding of the planning process and of the particular performance measures being discussed. Usually, an AHP procedure can use either a single set of responses obtained through consensus from the group of decision makers or an average of the responses [13]. For this process, the individual responses were collected from each decision maker, with a view of examining the trends and similarities between them, and later translated to a single set of responses to derive the value function.

The two selected performance measures are indicated in Table I and represented those that were easily understood by the group of decision makers, and for which the application of nonlinear utility scaling made the most sense. The first measure selected, quantifies the daily emissions of the oxides of nitrogen (NO_x), carbon monoxide (CO), and volatile organic compounds (VOC). The other measure quantifies the proportion of total person-miles of travel that is in a non single occupant vehicle (SOV). For the emissions measure, it is generally accepted that the benefits of reducing emissions at the "worse" end of the spectrum should be given greater importance. It was felt that the input of decision makers in assessing how the value of the measure varies would be useful. Similarly, for the measure considering SOV travel—it is well known that in the United States, a majority of transportation occurs as SOV (automobile) travel. Thus, it was felt that it was appropriate to introduce nonlinear scaling to reflect the decision makers' perspective on how best the credit increases in non single-occupant travel. The process of deriving the utility function is described in detail for the emissions measure, while only the results are presented for the measure concerning non-SOV travel.

C. Derivation of Value Function for Daily NO_x, CO, and VOC Emissions

This performance measure quantifies the total daily emissions of NO_x, CO, and VOC due to automobile emissions per mile of roadway. It is expressed as grams per mile, and the combined measure is arrived at by weighting the emissions of each pollutant according to their respective pollutant damage costs. The scaling extremes, i.e., the projected best case scenario and worst case scenario for this particular measure correspond to the combined emission levels of 1.28 and 180.5 kg/mi, respectively. Based on this knowledge, two points on the curve can be fixed, as shown in Fig. 3.
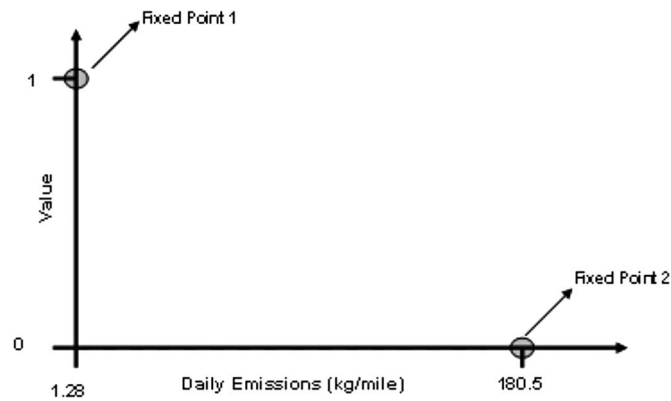
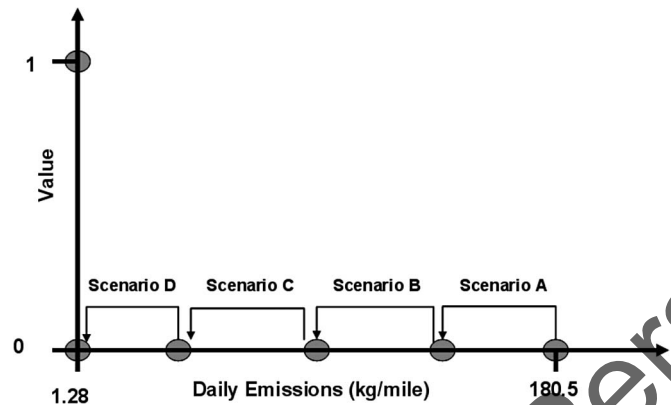Fig. 3.   Fixed points on value-curve for emissions.

Fig. 4.   Scenarios defined for the emission performance measures.

To derive a value function between these two points, the range of values on the x-axis is split into four increments. The case of reducing emissions at each increment is termed as a scenario. For example, Scenario X could be defined as reducing daily emissions from 181 to 125 kg/mi, while Scenario Y could be defined as reducing emissions from 125 to 100 kg/mi. Based on knowledge of the performance measure and its variation, it is possible to compare the relative desirability or importance of the scenarios. This strength of preference is expressed on a numerical scale 1–9, using a set of guidelines as devised by Saaty [14]. A score of 1 implies that both scenarios are equally important, and a score of 9 implies that one scenario is absolutely more important than the other. Pair-wise comparisons are made for each pair of defined scenarios, and the results are used to populate an AHP matrix, from which the weights for each of the scenarios (totaling to 1) can be obtained. Since the utility values are also on a 0–1 scale, the weights for each scenario thus represent their incremental value, from which the value curve can be derived. The AHP matrix can also be used to check for consistency in a set of responses, and to rectify any inconsistencies in the decision-making process.

For the emission measures, four scenarios are defined covering the range of possible emission levels between the best and worst case projections (see Fig. 4).

Table II provides the numerical details of each scenario. Verbal descriptors were used (ranging from "very bad," "bad,"

Scenario	Description of Improvement	
	Daily Emissions	Verbal Descriptor*
A	180.50 kg/mile to 135.70 kg/mile	Very Bad to Bad
B	135.70 kg/mile to 90.89 kg/mile	Bad to Moderate
C	90.89 kg/mile to 46.09 kg/mile	Moderate to Good
D	46.09 kg/mile to 1.28 kg/mile	Good to Very Good

*The verbal descriptors were further described to the decision maker in technical terms, specific to the performance measure in question.

Scenario	A	B	C	D
A	1.00	5.00	7.00	9.00
B	0.20	1.00	5.00	7.00
C	0.14	0.14	1.00	3.00
D	0.11	0.20	0.14	1.00

"moderate," "good," and "very good") to describe the levels of attainment for each scenario. The verbal descriptors were further described to the decision makers specific to the performance measure in question. For example, for the emission measures, the "very bad" scenario represented the kind of emissions associated with heavy, highly congested traffic, while the "very good" scenario was represented by emissions associated with free flowing, lower volume traffic conditions. Intermediate scenarios were also similarly described in a manner that the decision makers were able to understand. Decision makers were asked to perform a total of six pair-wise comparisons on the AHP scale, for all possible combinations of the scenarios. Based on the responses, an AHP matrix can be compiled and used to calculate points on the curve, and checked for consistency.

Rather than providing decision makers with scenarios related to actual levels of the performance measurement, an alternative approach could have been adopted to relate the performance measure (in this case, emissions) to the cost of impacts (such as health, environmental damage). However, the AHP process proposed is based on deriving the decision makers' perception of how the value of a measure varies as the measure itself varies. Given this, it was felt that consideration of the measure rather than the costs was preferable, because decision makers may tend to judge quantities expressed as costs having a linear variation of utility.

1) Construction of AHP Matrix and Derivation of Values: The AHP matrix is a square matrix of order equal to the total number of options evaluated (in this case, four scenarios). The rows and columns represent each scenario, and each cell of the matrix represents the degree to which the row component dominates the column component on the AHP scale. If the column component is the dominant option, the reciprocal of the AHP scale score is entered as the cell value instead. The diagonal values of the AHP matrix are always unity, as each element is equally important when compared to itself ($= 1$ on the AHP scale). Table III shows the AHP matrix used to derive the value

TABLE IV
NORMALIZED EIGENVECTOR FOR RELATIVE PRIORITIES

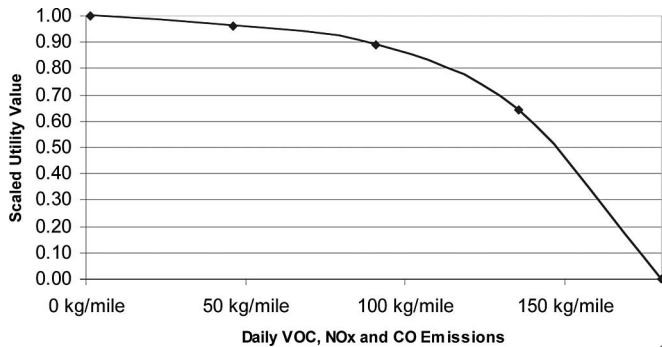| Scenario	Relative Priority (Eigen Vector)	Cumulative Priority (Utility Curve)
A	0.64	0.64
B	0.25	0.88
C	0.08	0.97
D	0.04	1.00

Fig. 5.   Value function plotted from results of AHP evaluation- emission measures.

function, and is based on the responses from the six individual decision makers.

For this matrix, the normalized Eigenvector represents the relative desirability of the different scenarios (each of which represents a specific increment in the performance measure value). Thus, the location of various points on the curve can be determined, from which a function can be derived. Table IV shows the calculated values used to identify points on the curve, and Fig. 5 shows the shape of the value function derived.

2) Checking for Consistency: The consistency of responses obtained from the AHP can be checked by calculating the consistency index (CI) and consistency ratio (CR), as shown in (1) and (2), respectively. Generally, CR values below 0.1 indicate a good degree of consistency in the pair-wise comparisons. The CI and CR values for this measure are 0.09 and 0.1, respectively, which are found to be satisfactory.

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{1}$$

$$CR = \frac{CI}{RI} \tag{2}$$

where

n = order of matrix;

$\lambda_{\max}$ = principal Eigenvalue of AHP matrix;

RI = random index −0.9 for matrix of order 4.

3) Deriving Equation for Value Function Based on AHP Results: Based on the data points obtained from the AHP, a value function is derived using a method of least squares estimation
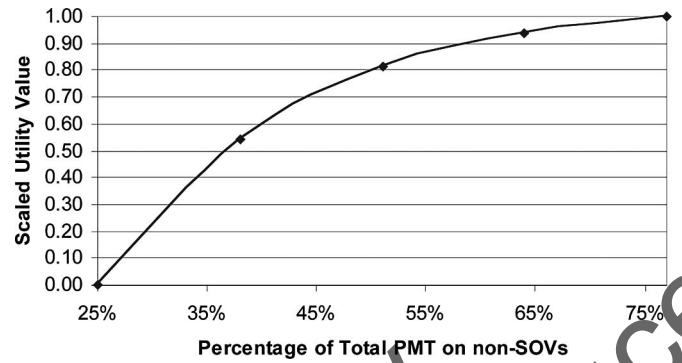

Fig. 6.   Value function based on results of AHP evaluation- non-SOV travel measure.

(see (3)).

$$y = 1.019 - 0.018e^{0.022x} \tag{3}$$

where

y = scaled value;

x = combined VOC, NO$_x$, and CO emissions, in kg/mi.

D. Derivation of Value Function for Proportion of Non-SOV Travel

This performance measure quantifies the proportion of total daily person miles of travel that occurs in a non-SOV (this includes higher automobile occupancies, as well as bus and rail transit). The best and worst case scenarios for this measure are defined based on attaining overall equivalent automobile occupancy levels of 1.63 and 1.14 corresponding to figures from the latest *National Household Travel Survey* [19]. These values translate the performance measure values of 77% and 25% as the best and worst cases, respectively. The value function for this measure is derived using the same technique as for the previous measure. Fig. 6 shows the curve for this measure. The CI and CR values were 0.066 and 0.073, respectively, indicating a fairly high level of consistency.

Equation (4) shows the value function derived for this performance measure.

$$y = 1.059 - 4.249e^{-5.558x} \tag{4}$$

where

y = scaled value;

x = percentage of total person miles of travel that is in a non-SOV.

E. Summary of the Scaling Process

The process of scaling of various performance measures was discussed in this section. Some of the performance measures (expressed as a percentage, or on a 0–1 scale) already reflected their scaled values. For other measures, linear scaling was considered for the majority, while a methodology for deriving nonlinear value functions for scaling was proposed, and demonstrated for two selected measures.

TABLE V
COMPARISON OF SCALED VALUES FOR MEASURES AND AGGREGATE INDEX

Comparison for Emissions Measure							
	Base Case Scenario				Future Case Scenario		
Link	Scaled Value for Measure		Percentage Change over Linear	Absolute Difference	Scaled Value for Measure		Percentage Change over Linear	Absolute Difference
	Non Linear Value Curve	Linear Value Curve			Non Linear Value Curve	Linear Value Curve		
1	0.68	0.13	423%	0.55	0.97	0.73	33%	0.24
2	0.77	0.22	250%	0.55	0.97	0.7	38%	0.27
3	0.96	0.63	52%	0.33	0.98	0.82	20%	0.16
4	0.96	0.67	43%	0.29	0.99	0.87	14%	0.12
Total Section	0.86	0.36	139%	0.5	0.98	0.76	29%	0.22
Comparison for Non-SOV Measure							
	Base Case Scenario				Future Case Scenario		
Link	Scaled Value for Measure		Percentage Change over Linear	Absolute Difference	Scaled Value for Measure		Percentage Change over Linear	Absolute Difference
	Non Linear Value Curve	Linear Value Curve			Non Linear Value Curve	Linear Value Curve		
1	0.6	0.29	107%	0.31	0.6	0.29	107%	0.31
2	0.6	0.29	107%	0.31	0.6	0.29	107%	0.31
3	0.6	0.29	107%	0.31	0.6	0.29	107%	0.31
4	0.6	0.29	107%	0.31	0.6	0.29	107%	0.31
Total Section	0.6	0.29	107%	0.31	0.6	0.29	107%	0.31
Comparison for Aggregate Index Value							
	Base Case Scenario				Future Case Scenario		
Link	Index Value		Percentage Change over Linear	Absolute Difference	Index Value		Percentage Change over Linear	Absolute Difference
	With Non Linear Value Curves	All Linear Value Curves			With Non Linear ValueCurves	All Linear Value Curves		
1	0.54	0.43	26%	0.11	0.38	0.33	15%	0.05
2	0.65	0.54	20%	0.11	0.36	0.3	20%	0.06
3	0.58	0.51	14%	0.07	0.55	0.51	8%	0.04
4	0.57	0.51	12%	0.06	0.65	0.63	3%	0.02
Total Section	0.6	0.5	20%	0.1	0.41	0.36	14%	0.05

IV. RESULTS AND DISCUSSION

To assess the impact of using the derived nonlinear utility functions instead of assuming linear utility functions for the selected performance measures, two comparisons were performed and discussed in the following sections.

A. *Comparison of the Difference in Scaled Values for the Individual Measures*

A comparison between the scaled values for the emissions performance measure using the value function that was derived, and assuming a linear variation, is presented in Table V. The comparisons are shown for both the base and the future cases,

and for the entire case study corridor, as well as in the corresponding sections. For this measure, it was seen that the scaled value using the derived functions varied from the linear assumption by a magnitude ranging from 14% to 423%. The range of variation can be attributed to the variations of the quantified measure between the base and the future cases, and among various roadway segments. There was less variation that could be inferred from the measure relating to the proportion of non-SOV travel, as the quantified performance measure was the same for all links on the section, for both the base and the future cases, respectively. However, there was a 107% increase in the scaled measure value, when the nonlinear utility function was used instead of a linear utility function.

B. Comparison of the Difference in the Total Index Value

The aggregate index value is calculated as the weighted sum of the individual scaled measures. The set of 13 measures applied to the study corridor are assigned individual weights (adding to 1), thus, the aggregate index value is also expressed on a 0–1 scale. The index value is calculated for the case study, considering the nonlinear scaling for the two measures, and is compared with the index value calculated by assuming linear utility functions for the two measures also. The findings are also shown in Table V. It is seen that the index values are impacted ranging from a magnitude of 3% to 26%. This represents degrees of varying impact on the final results, and is a lesser range of values when compared to those from individual measures. However, it is still observed that the consideration of nonlinear scaling for even a small subset of measures can affect the outcome of the overall MCDM analysis.

V. OBSERVATIONS AND CONCLUSION

It can be seen that taking into account the nonlinearity of utility can significantly impact the results in terms of the scaled value for a quantified measure. The aggregated sustainability index is made up of a set of performance measures, most of which are scaled using linear utility functions. However, the derivation and assumption of nonlinear utility functions, even for just two performance measures out of a total of thirteen is found to impact the final aggregate index value in most cases. It is fairly obvious that the nature and the magnitude of the impact depend upon the values of the individual measures quantified for a particular case. Another factor that can affect the result is the weights assigned to the different measures. It can still be concluded, however, that the use of nonlinear utility functions for performance measures in the MAUT analysis can significantly impact the results and findings.

In summary, the following are indicated from the findings in this paper.

1) While the MAUT provides a suitable decision-making methodology for transportation planning applications, it is indicated that the results from an MAUT analysis can be significantly impacted by how the scaling is performed for individual performance measures.

2) The extent of the difference between linear and nonlinear scaling for a performance measure is dependent upon the value of the performance measure itself (i.e., where it lies on the value curve). This indicates that the construction of value functions needs to be given importance.

3) The proposed AHP-based methodology requires a single questionnaire input from the decision makers to elicit value functions, which provides a useful alternative to direct rating and other approaches that sometimes require "back and forth" interaction to construct a function.

4) However, given the extent to which input from the decision makers plays a role in this process (from the selection of performance measures, to assigning weights, and providing input for the construction of functions), it is necessary that the decision makers are objective and do not introduce any bias. The authors posit that providing the questionnaires and formalizing the decision-making process helps preventing bias to a certain extent, as it allows the decision makers to consider their thought processes instead of relying solely on intuitive judgments.

A. Limitations and Scope for Further Research

Careful consideration of the utility variations assumed in a performance measurement-based analysis needs to be warranted. In this respect, the AHP-based procedure proposed in this paper provides a possible methodology for assessing the value functions. This methodology allows certain performance measures to be scaled according to how the decision makers' values improve a measure, relative to their own assessment of the measure's value. Although the AHP process might be considered as an unconventional tool to be used in this context and is controversial among some researchers in the MCDM field, it was found to be fairly straightforward to implement and we are fairly confident that results (linearity versus nonlinearity comparison) would not change much by using alternative elicitation methods. It would be interesting to see a comparison between alternative techniques and further research into the assessment of value and utility functions, specifically developed for transportation planning applications. This would prove useful to improve how MCDM methodologies are approached in transportation sector. Also, the results and findings were compared only for a single case study corridor. The expansion to include other cases will also serve to further strengthen this research.

REFERENCES

[1] M. Meyer and E. Miller, *Urban Transportation Planning: A Decision Oriented Approach*. New York: McGraw-Hill Higher Education, 2001.
[2] D. Bell, R. L. Keeney, and H. Raiffa, *Conflicting Objectives in Decisions*. New York: Wiley, 1977.
[3] R. L. Keeney and H. Raiffa, *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*. New York: Wiley, 1976.
[4] D. Von Winterfeldt and W. Edwards, *Decision Analysis and Behavioral Research*. New York: Cambridge Univ. Press, 1986.
[5] J. Zietsman, L.R. Rilett, and S. Kim, "Transportation corridor decision making with multi-attribute utility theory," *Spec. Issue Int. J. Manage. Decision Making*, vol. 7, no. 2/3, pp. 255–266, 2006.
[6] C. Jeon, A. Amekudzi, and R. Guensler, "Sustainability assessment at the transportation planning level: performance measures and indexes," presented at the 87th Annu. Meet. Transp. Res. Board, Washington, DC, 2008.
[7] S. Leleur and N. Berg, "The COSIMA approach to transport decision making: combining cost-benefit and multi-criteria analysis for comprehensive project appraisal," presented at the Korean Dev. Inst. World Bank Conf., Seoul, South Korea, 2007.
[8] W.R. Black, "Toward a measure of transport sustainability," presented at the 79th Annu. Meet. Transp. Res. Board, Washington, DC, 2000.
[9] Yale University. (2005) *2005 Environmental Sustainability Index: Benchmarking national environmental stewardship*. New Haven, CT: Yale Center for Environmental Law and Policy, Yale University, [Online]. Available: http://www.yale.edu/esi/ESI2005_Main_Report.pdf

[10] P. C. Fishburn, *Utility Theory for Decision Making*. New York: Wiley, 1970.

[11] E. Triantaphyllou, *Multi-Criteria Decision Making Methods: A Comparative Study*. The Netherlands: Kluwer, 2001.

[12] P. Yu, *Multiple Criteria Decision Making: Concepts, Techniques and Extensions*. New York: Plenum, 1985.

[13] R. Accorsi, E. Zio, and G. E. Apostolakis, "Developing utility functions for environmental decision making," *Prog. Nucl. Energy*, vol. 34, no. 4, pp. 387–411, 1999.

[14] T. L. Saaty, *The Analytic Hierarchy Process*. New York: McGraw-Hill International, 1980.

[15] T. L. Saaty and L. G. Vargas, *Models, Methods, Concepts and Applications of the Analytic Hierarchy Process*. Norwell, MA: Kluwer, 2001.

[16] K. Fischer. (2005). *Value Functions versus Utility Functions*. Birmingham, UK: Aston University, [Online]. Available: http://www.abs.aston.ac.uk/newweb/research/publications/docs/RP0416.pdf

[17] J. Zietsman, W. Knowles, T. Ramani, B. Bochner, and J. Lee, "Sustainability enhancement tool for state DOTs using performance measurement," presented at the 87th Annu. Meet. Transp. Res. Board, Washington, DC, 2008.

[18] T. Ramani, "An improved methodology for multi-criteria assessments of highway sustainablity," M.S. Thesis, Texas A&M Univ., College Station, Texas, 2008.

[19] P. Hu, and T. R. Reuscher. (2004, Dec.). *Summary of Travel Trends: 2001 National Household Travel Survey*. [Online]. Available: http://nhts.ornl.gov/2001/pub/STT.pdf

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