Modeling Infrastructure Performance and User Costs

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Abstract: An infrastructure-performance-deterioration model predicts the performance of infrastructure facilities such as bridges, railroad, and highways as a function of explanatory variables such as inherent infrastructure characteristics (material properties, construction quality), ambient climate, usage of the facility, etc. However, there is no unambiguous approach to measuring directly the performance of the facility, and hence we consider performance to be unobservable (latent). The problem of developing performance-deterioration models includes the definition of the aforementioned unobservable performance in terms of the measurable distress measures of the facility, and simultaneously relating the performance to the explanatory variables. In this paper, we extend previous research to include user costs (costs accruing to the users of the infrastructure facility) in the modeling framework. Hence, an integrated performance and user-cost model system is developed, and a case study is conducted on a highway example using data from Brazil compiled by the World Bank. Although, the case study is on highways, the methodology is general and applicable to any deteriorating facility with measurable distress measures and explanatory variables.

INTRODUCTION

The determination of cost-effective maintenance actions for infrastructure facilities requires information on

- Current condition (obtained from an inspection of the facility)
- Anticipated future conditions under different maintenance and rehabilitation actions and their associated costs (obtained from performance deterioration models)
- Impacts of the condition of the infrastructure facility on user costs (obtained from user cost models)

The emergence of automated condition measurement technologies (such as video, laser, radar, and infrared technologies) has made available large quantities of data for the analysis of infrastructure performance. These new technologies require new methods to process their nascent output to a manageable size meaningful for decision-making. For example in railroads, new automated technologies, such as electronic rail profile measurement, provide large quantities of detailed rail condition data. On the other hand, existing approaches to performance and user cost analysis are usually based on subjective indices using a predetermined set of distress measures [e.g., for highway pavements, measures like Present Serviceability Index (Carey et al. 1960), Pavement Condition Index (Shahin and Kohn 1981)]. There is a need for an improved performance and user-cost analysis methodology to exploit these enhanced data-collection capabilities. The first step to meet this need is the latent infrastructure performance deterioration modeling approach (Ben-Akiva and Ramaswamy 1989, 1993) wherein performance is characterized by a latent variable. The approach is flexible enough to incorporate distress measurements from new technologies in the calibration of a performance index.

In this paper, we extend the Ben-Akiva and Ramaswamy framework to estimate user-cost models, which relate the costs accruing to the users of the infrastructure facility as a function of the performance of the facility, simultaneously with performance deterioration models.

BACKGROUND: INFRASTRUCTURE MANAGEMENT PROCESS

The infrastructure-management problem consists of the allocation of limited resources for the maintenance and rehabilitation of different facilities both over spatial and temporal dimensions. The different facets of the infrastructure management process are described in Ben-Akiva et al. (1991, 1993).

The process can be divided into three task areas: (1) Data collection and analysis (including

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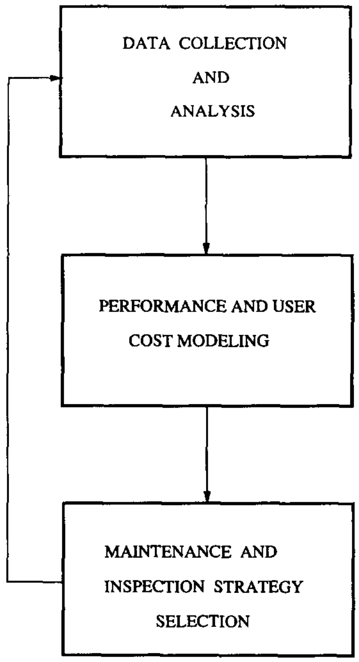

FIG. 1. Infrastructure Management Process

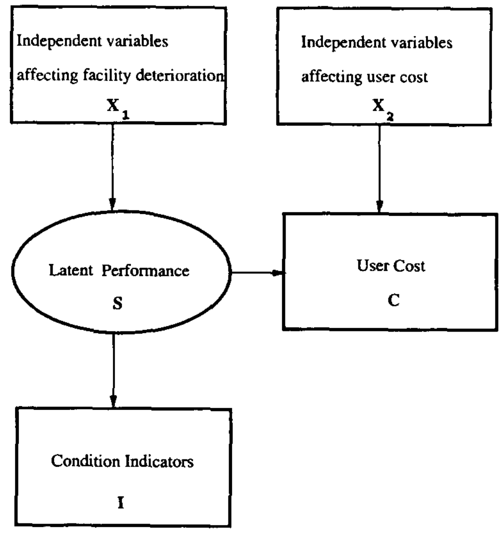

FIG. 2. Infrastructure Performance and User-Cost Model

inspection); (2) performance and user-cost analysis and prediction; and (3) maintenance and rehabilitation (M&R) and inspection strategy selection.

These tasks are related in the manner shown in Fig. 1. The facility condition data collected using different technologies is used in two ways. First, it is one of the items used in the estimation of infrastructure performance and user-cost models. Second, it provides the initial values in the prediction of future performance and life-cycle costs (M&R, inspection, and user costs). In addition to M&R strategies, the third block includes models for selection of future inspection strategies. This effect is represented by the feedback loop of Fig. 1.

Data Collection and Analysis

Data is collected on the extent of facility damage (such as area, length, and severity of damage), on the causal variables that affect deterioration such as facility type, usage, age, and environmental conditions, on the costs of performing maintenance, and the impacts on the user arising from the deterioration of the facility. The condition data may be collected by visual inspection, through manual measurements or through automated techniques. The data collected, after suitable processing, can be used as inputs to performance and user cost models. The data collected can also be used for monitoring purposes to validate model predictions and update a model system after it has been implemented.

Performance and User Cost Modeling

A deterioration model links a measure of condition of the facility to a vector of explanatory variables. The condition measure in its simplest form is just the extent of damage; more-complex indices that combine the extents of different damage types may also be used. Similarly, a user-cost model measures the impact of deterioration on the user as a function of the condition of the facility. The economic analysis of an infrastructure facility improvement project requires two critical inputs. They are

1. The M&R costs accruing to the agency operating the facility for improving the condition of the facility. These costs, known as agency costs, are easily quantifiable as a function of the different M&R actions.
2. The decrease in the costs accruing to the users of the facility as a result of the facility condition improvement. These costs, known as user costs, are not readily quantifiable, and models relating these costs to the condition of the facility are necessitated.

This paper addresses the issue of estimating the models needed to estimate the second input in the economic analysis of infrastructure facility improvement. Hence we concentrate on this block of the infrastructure management process.

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M&R and Inspection Strategy Selection

This block involves the selection of an optimal maintenance and inspection strategy that minimizes the total costs (maintenance, inspection and user costs) over the planning horizon subject to various resource and technical constraints. A methodology that recognizes the trade-offs between inspection costs (which increase with the accuracy of the measurement technology used) and the added costs of maintenance and rehabilitation (which decrease with increased accuracy of the information provided by this technology) in order to address the inspection decisions in a systematic manner is presented in Madanat and Ben-Akiva (1994).

JOINT MODEL FOR PREDICTING INFRASTRUCTURE PERFORMANCE AND USER COSTS

The framework for the simultaneous estimation of infrastructure performance deterioration and user-cost models is presented in Fig. 2. $\mathbf{X}_1$ are the independent variables that are expected to affect the performance of the facility. Since the true performance of the facility is unobserved it is characterized by a latent vector $\mathbf{S}$. We allow for a multidimensional performance characterization to represent different performance components such as structural integrity, functional performance (service quality), etc. The factors affecting the performance of the facility can be broadly classified into the following categories: (1) Inherent factors: factors associated with the facility itself like facility type, construction quality, etc.; and (2) extraneous factors: include facility usage, maintenance actions performed, environmental factors, etc. The main problem in estimating a performance model is that it is not directly observable. Instead, what can be observed by inspecting the facility are condition distress measures $\mathbf{I}$. For example, in the highway context, the observed distress measures include roughness, cracking, rutting, surface patching, and raveling. These distress measures are assumed to be manifestations of the latent performance $\mathbf{S}$, and hence called condition indicators. The user costs $\mathbf{C}$ depend on the performance of the facility and a set of independent variables $\mathbf{X}_2$. In the highway example, $\mathbf{X}_2$ includes highway geometry (horizontal and vertical alignment), traffic composition, traffic volume, factor costs such as labor, fuel, and so on. The relationships among the latent performance $\mathbf{S}:(M \times 1)$, user costs $\mathbf{C}:(T \times 1)$, and the explanatory variables $\mathbf{X}_1:(K_1 \times 1)$ and $\mathbf{X}_2:(K_2 \times 1)$ form the structural model. The mapping from the latent performance $\mathbf{S}$ to the indicators $\mathbf{I}$: $(P \times 1)$ form the measurement model. Using linear functional forms the model system is written as follows.

Structural Model

$$\mathbf{S} = \mathbf{\Gamma}\mathbf{X}_1 + \boldsymbol{\zeta}_1; \qquad \mathbf{C} = \boldsymbol{\alpha}\mathbf{S} + \boldsymbol{\beta}\mathbf{X}_2 + \boldsymbol{\zeta}_2 \tag{1, 2}$$

Measurement Model

$$\mathbf{I} = \mathbf{\Lambda}\mathbf{S} + \boldsymbol{\varepsilon} \tag{3}$$

where $\mathbf{\Gamma}:(M \times K_1)$, $\boldsymbol{\beta}:(T \times K_2)$, $\boldsymbol{\alpha}:(T \times M)$, and $\mathbf{\Lambda}:(P \times M)$ = parameter matrices to be estimated; $\boldsymbol{\zeta}_1:(M \times 1)$ and $\boldsymbol{\zeta}_2:(T \times 1)$ = error components in the structural model; and $\boldsymbol{\varepsilon}:(P \times 1)$ = error component in the measurement model. It must be noted that the key link between the structural and the measurement models is the latent performance $\mathbf{S}$. The structural and the measurement models together form a latent variable model system. Without any loss of generality all observed variables are written as deviations from their respective means. Else intercepts must be included in both the structural and measurement models. See the appendix for a brief review of latent variable models and estimation of the model parameters.

CASE STUDY: APPLICATION TO HIGHWAY PAVEMENTS

Description of Data

The data used in this study was collected during the World Bank road deterioration studies undertaken in Brazil during 1975–82 under a program called "Research on the Interrelationships between Costs of Highway Construction, Maintenance and Utilization" (GEIPOT 1982).

Surfacing Type

There were 3,149 observations (an average of 8.3 observations per highway section—one lane, 280–560 m long—at approximately half-yearly intervals) of the pavement condition, cumulative traffic, environmental factors, maintenance status, and pavement strength at given dates as they evolved during the study period. There were four main types of pavement surfaces at first observation dates: (1) Asphalt concrete original; (2) double surface treatment original; (3) asphalt concrete overlay on original asphalt concrete surfacing; and (4) asphalt concrete overlay on original double surface treatment.

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Explanatory Variables

The important explanatory variables, which affect performance deterioration, available in the data set are

1. Age since most recent rehabilitation measured in years (*AGER*).
2. Cumulative number of equivalent standard axles (*ESAXL*), since most recent rehabilitation, at the date of observation.
3. Cumulative precipitation since most recent rehabilitation (*CP*) in meters.
4. Structural number (*SNC*), a measure of pavement strength, obtained from the thickness and stiffness of different pavement layers.

Condition Indicators

The indicators of pavement performance are roughness, cracking, rutting, surface patching, and raveling. Roughness (*RQI*), a measure of the longitudinal irregularity of the road surface, is measured in quarter-car index with units in count/km. As a measure of cracking, area of indexed cracking (*CRX*) as percent of surface area is also available. Rutting (*RDMN*) is measured as the mean rut depth under 1.2 m straight edge across two wheel paths and four test points per wheel path. Surface patching (*SPAT*) is measured as the sum of the areas of surface patching expressed as percent of surface area of the section. Raveling (*RAV*) is measured as sum of the areas ravelled expressed as percent of the section area. The indicators of highway pavement strength are Benkelman deflection (*DEFS*) and rut depth. The descriptive statistics of selected variables are given in Table 1.

Data on User Costs

In this paper, the term "user costs" in the highway context refer to the vehicle operating costs with the following components: (1) Fuel consumption; (2) tire wear; (3) maintenance parts; (4) maintenance labor; and (5) lubricant oil consumption.

The vehicles are grouped into two main categories: (1) Cars and utilities; and (2) buses and trucks. Fuel consumption for each vehicle category is in terms of liters of fuel consumed for 1,000 vehicle-km (*FCCU* and *FCBT*) on a highway segment with given damage conditions and geometric design. Tire wear data (*TWCU* and *TWBT*) are in terms of number of new tires consumed per 1,000 vehicle-km. Cost of maintenance parts for each vehicle category (*MPCU* and *MPBT*) data are in the form of fraction of the average price of a new vehicle of the same category for 1,000 vehicle-km. The data on maintenance labor (*MLCU* and *MLBT*) is in labor-hours for 1,000 vehicle-km, while lubricant oil consumption (*LCU* and *LBT*) is in liters per 1,000 vehicle-km. Further these data are converted into user costs in dollars (*UCCU* and *UCBT*) per 1,000 vehicle-km for each vehicle category. Of the five user-cost components, the dominant components are fuel costs, maintenance parts costs and maintenance labor costs. The only variable available to represent the effects of highway geometry on vehicle operating costs is average vertical gradient (*GRAD*) of the roadway.

In the following sections, estimation results of simultaneous performance and user cost models are presented. It must be noted that in all the estimated models, the covariance matrix of the error term in the structural model is unconstrained (all the elements are free parameters to be estimated). This specification aids in capturing the effects of unobserved factors on the different performance components. On the other hand, by the assumption of conditional independence of the indicators (as discussed in the appendix) the covariance matrix of the error terms in the measurement model is constrained to a diagonal matrix. This is a realistic assumption as the measurement processes for the different indicators are independent, and the observed corre-

TABLE 1. Descriptive Statistics of Selected Variables

Variable (1)	Units (2)	Mean (3)	Standard deviation (4)	Minimum (5)	Maximum (6)
Age since rehabilitation	years	8.19	4.53	0.007	23.05
Equivalent standard axles	356 GN load	2.226	3.2	0.00011	30.28
Cumulative precipitation	meter	2.58	1.92	0.00	7.22
Gradient	%	2.6	2.3	0.1	6.8
Roughness	QI in count/km	40.53	15.36	12.92	99.69
Cracking	% surface area	15.16	25.70	0.00	100.00
Rut depth	mm	3.71	2.19	0.00	15.75
Surface patching	% surface area	2.47	8.65	0.00	86.29
Raveling	% surface area	7.61	19.70	0.00	100.00
Benkelman deflection	mm	0.65	0.36	0.12	2.03
Structural number	units	4.12	1.03	1.62	7.73

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lations among the indicators are due to their dependence on the common latent performance variables. Also, all the models are estimated using the unmaintained sections only.

Estimated Models

In this section, estimation results are presented for the case wherein aggregate user costs for each vehicle category in dollars are used as dependent variables, followed by estimated models wherein the dominant components of the user costs for each vehicle category are utilized as dependent variables.

Aggregate User-Cost Models

Single Latent Performance Model: Model 1-1. In this model, the performance of the pavement is characterized by a single latent variable, and is specified to be affected by the age of the pavement since last rehabilitation (*AGER*), cumulative precipitation since last rehabilitation (*CP*), cumulative number of equivalent standard axles (*ESAXL*) (which represents traffic loading or usage of the highway), and structural number (*SNC*) (which is a measure of pavement strength). One would expect a stronger pavement to have a slower rate of deterioration compared to a weaker pavement. Therefore, the explanatory variables *AGER*, *ESAXL*, and *CP* are divided by *SNC* to capture these effects. User costs (aggregate costs in dollars) for each vehicle category is written as a function of the latent performance of the pavement and the vertical alignment of the highway segment. These three equations form the structural model of the model system.

In the measurement model, the observed damage measurements—roughness (*RQI*), cracking (*CRX*), rut depth (*RDMN*), surface patching (*SPAT*) and raveling (*RAV*)—are used as indicators of the latent performance of the pavement segment. Since the latent variable is unobserved it does not have a definite scale. Hence it is necessary to fix one parameter in each column of the Λ matrix in the measurement model to unity. This defines the unit of measurement of the latent variable to be the same as the corresponding observed variable. In this model the scale of the performance variable is set to that of roughness. The structural and the measurement models are given as follows.

Structural Model

$$S = \gamma_1 AGER/SNC + \gamma_2 ESAXL/SNC + \gamma_3 CP/SNC + \zeta_1 \tag{4}$$

$$UCCU = \alpha_1 S + \beta_1 GRAD + \zeta_2; \qquad UCBT = \alpha_2 S + \beta_2 GRAD + \zeta_3 \tag{5, 6}$$

Measurement Model

$$RQI = S + \varepsilon_1; \qquad CRX = \lambda_2 S + \varepsilon_2; \qquad RDMN = \lambda_3 S + \varepsilon_3 \tag{7–9}$$

$$SPAT = \lambda_4 S + \varepsilon_4; \qquad RAV = \lambda_5 S + \varepsilon_5 \tag{10, 11}$$

The estimated structural model is presented in Tables 2 and 3, the measurement model in Table 4, and the extracted performance model in Table 5. The coefficients of all the explanatory variables in the structural deterioration model are significant. The fit of the deterioration model as measured by the squared multiple correlation (SMC)—a measure of goodness of fit analogous to R^2 in regression models—is 0.62. All the coefficients of the user cost models are significant and have the expected signs. The fit of the user cost equation for cars and utilities is good with SMC of 0.93, while the fit of the corresponding equation for buses and trucks is 0.55. The ratios of the parameters of latent performance and gradient variables in the user cost equation for buses and trucks to the corresponding parameters in the user cost equation for cars and utilities, are approximately 100 and 5, respectively. This is interpreted as pavement performance having relatively greater impact on the user costs of buses and trucks compared to the gradient variable.

In the measurement model, the SMC of any equation is a measure of the variance of the indicator explained by the latent variable, a higher value of SMC for a particular measurement equation implies that the associated indicator is a better measure of the latent variable than an indicator with lower value of SMC. In this model, roughness, cracking, and rut depth have relatively high SMC of approximately 0.4. On the other hand, patching and raveling appear to be poor measures of the latent performance of the pavement.

In the equation for the estimated value of latent performance as a function of the indicators, the coefficients for the different indicators are calculated using the full information extraction method described in Gopinath (1992). The SMC for this extracted performance model is 0.69 with all the coefficients, except surface patching coefficient, statistically significant. It can be seen that the *t*-statistics of roughness, cracking and rut depth are more than those of patching and raveling reiterating the relative importance of the former measures. This model can be used to estimate the performance given the distress measurements from an inspection of the facility.

Two-Component Latent Performance Model: Model 1-2. In this specification, it is hypothesized that the functional performance of the pavement is characterized by a latent variable

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TABLE 2. Model 1-1, Structural Model: Performance

Independent variable (1)	Estimate (2)	t-statistic (3)
AGER/SNC	3.562	17.34
ESAXL/SNC	3.897	11.67
CP/SNC	1.654	4.13

Note: Squared multiple correlation = 0.62.

TABLE 3. Model 1-1, Structural Model: User Cost

Dependent variable (1)	Latent performance (2)	Gradient (3)	Squared multiple correlation (4)
User costs for cars and utilities	0.375 (15.37)[a]	7.582 (149.89)[a]	0.93 —
User costs for buses and trucks	40.397 (36.54)[a]	41.745 (19.23)[a]	0.55 —

[a]t-statistics in parentheses.

TABLE 4. Model 1-1, Measurement Model

Indicator (1)	Estimate (2)	t-statistic (3)	Squared multiple correlation (4)
Roughness	1.000	—[a]	0.37
Cracking	1.503	17.87	0.35
Rut depth	0.167	20.23	0.45
Surface patching	0.256	9.65	0.09
Raveling	0.531	7.34	0.04

[a]Fixed parameter.

TABLE 5. Model 1-1, Extracted Performance Model

Indicator (1)	Estimate (2)	t-statistic (3)
Roughness	0.181	18.33
Cracking	0.135	18.65
Rut depth	1.978	29.56
Surface patching	0.035	1.76
Raveling	0.073	9.54

Note: Squared multiple correlation = 0.69; total number of observations = 1,571.

S_{func} and the structural integrity of the pavement is characterized by another latent variable S_{struc}. The functional aspect is related to the surface characteristics such as roughness, cracking, raveling, etc., which affect user costs. The structural aspect is of no perceptible concern to the user, whereas it is extremely important to the highway agency because the future functional performance depends on the present structural condition. Further, the maintenance actions could be chosen with the objective of improving the functional performance (crack filling, resurfacing, thin overlay) and/or improving the structural performance (preventive maintenance, reconstruction). The indicators of latent functional performance are those distress measurements which affect the user costs directly (usually surface distresses). The indicators of latent structural performance are those related to the strength of the pavement. The functional performance is specified such that it is affected by the age of the pavement, traffic loading, precipitation, and pavement strength. Similarly, the structural performance is specified as a function of age of pavement, traffic loading, and pavement strength. User costs for each vehicle category is a function of the pavement's latent functional performance and highway geometry.

Structural Model

$$S_{func} = \gamma_{11}AGER/SNC + \gamma_{12}ESAXL/SNC + \gamma_{13}CP/SNC + \zeta_1 \quad (12)$$

$$S_{struc} = \gamma_{21}AGER/SNC + \gamma_{22}ESAXL/SNC + \gamma_{23}CP/SNC + \zeta_2 \quad (13)$$

$$UCCU = \alpha_1 S_{func} + \beta_1 GRAD + \zeta_3; \qquad UCBT = \alpha_2 S_{func} + \beta_2 GRAD + \zeta_4 \quad (14, 15)$$

Measurement Model

$$RQI = S_{func} + \varepsilon_1; \quad CRX = \lambda_2 S_{func} + \varepsilon_2; \quad RDMN = \lambda_5 S_{struc} + \varepsilon_3 \quad (16\text{–}18)$$

$$SPAT = \lambda_3 S_{func} + \varepsilon_4; \quad RAV = \lambda_4 S_{func} + \varepsilon_5; \quad DEFS = S_{struc} + \varepsilon_6 \quad (19\text{–}21)$$

The estimated structural model is presented in Tables 6–8, the estimated measurement model in Table 9, and the extracted performance model in Table 10. The scale of S_{struc} is set to that of Benkelman deflection. The SMC of rut depth equation is 0.72 indicating rut depth is a good measure of structural performance. Further, SMC of the Benkelman deflection equation is 0.42 indicating deflection is also a reasonable measure of structural performance. SMC of roughness measurement equation is 0.50, from which one can infer that roughness is a good measure of functional performance of the pavement.

The significant explanatory variables affecting functional performance are age since rehabilitation and precipitation, while the coefficient of traffic loading has insignificant t-statistic. On the other hand, the important variables affecting structural performance are age since rehabilitation and traffic loading, while precipitation coefficient is insignificant.

The user cost equations for cars and utilities, and buses and trucks have good fits with SMCs of 0.95 and 0.82, respectively. The fits of these equations, especially the user cost equation for buses and trucks, have improved compared to model 1-1.

Disaggregate User-Cost Models

Single Latent Performance Model: Model 2-1. In this model the dominant components of the user costs for each vehicle category are used as dependent variables in the structural model.

TABLE 6. Model 1-2, Structural Model: Functional Performance

Independent variable (1)	Estimate (2)	t-statistic (3)
AGER/SNC	4.345	16.87
ESAXL/SNC	0.418	0.98
CP/SNC	3.228	5.67

Note: Squared multiple correlation = 0.48.

TABLE 7. Model 1-2, Structural Model: Structural Performance

Independent variable (1)	Estimate (2)	t-statistic (3)
AGER/SNC	0.056	12.07
ESAXL/SNC	0.117	13.34
CP/SNC	0.000	0.19

Note: Squared multiple correlation = 0.43.

TABLE 8. Model 1-2, Structural Model: User Cost

Dependent variable (1)	Functional performance (2)	Gradient (3)	Squared multiple correlation (4)
User costs for cars and utilities	0.438	7.669	0.95
	(25.12)[a]	(169.53)[a]	—
User costs for buses and trucks	43.594	43.713	0.82
	(77.17)[a]	(29.83)[a]	—

[a]t-statistics in parentheses.

TABLE 9. Model 1-2, Measurement Model

	Functional Performance		Structural Performance		Squared multiple correlation
Indicator (1)	Estimate (2)	t-statistic (3)	Estimate (4)	t-statistic (5)	(6)
Roughness	1.000	—[a]	—	—	0.50
Cracking	1.385	19.76	—	—	0.39
Rut depth	—	—	8.864	15.32	0.72
Surface patching	0.306	12.45	—	—	0.15
Raveling	0.403	7.95	—	—	0.09
Benkelman deflection	—	—	1.000	—[a]	0.42

[a]Fixed parameters.

TABLE 10. Model 1-2, Extracted Performance Model

	Functional Performance		Structural Performance	
Indicator (1)	Estimate (2)	t-statistic (3)	Estimate (4)	t-statistic (5)
Roughness	0.371	66.23	—	—
Cracking	0.189	41.35	—	—
Rut depth	—	—	0.059	133.45
Surface patching	0.065	6.74	—	—
Raveling	0.104	15.63	—	—
Benkelman deflection	—	—	0.086	24.35
Squared multiple correlation	0.88		0.95	

Note: Total number of observations = 1,543.

TABLE 11. Model 2-1, Structural Model: Performance

Independent variable (1)	Estimate (2)	t-statistic (3)
AGER/SNC	3.567	16.89
ESAXL/SNC	4.103	11.78
CP/SNC	1.589	4.43

Note: Squared multiple correlation = 0.61.

TABLE 12. Model 2-1, Structural Model: User Costs

Category of vehicle (1)	Dependent variable (2)	Latent performance (3)	Gradient (4)	Squared multiple correlation (5)
Cars and utilities	fuel consumption	0.2792	24.91	0.96
	(liters)	(8.82)[a]	(199.59)[a]	—
	maintenance parts	3.86×10^{-6}	—	0.19
	(fraction of new vehicle)	(19.11)[a]	—	—
	maintenance labor	1.88×10^{-3}	—	0.19
	(hours)	(19.26)[a]	—	—
Buses and trucks	fuel consumption	−0.64	149.32	0.83
	(liters)	(−1.27)	(85.95)[a]	—
	maintenance parts	1.228×10^{-4}	—	0.86
	(fraction of new vehicle)	(97.10)[a]	—	—
	maintenance labor	0.3239	—	0.85
	(hours)	(95.9)[a]	—	—

Note: Total number of observations = 1,571.
[a]t-statistics in parentheses.

The dominant components modeled are fuel consumption, maintenance parts and maintenance labor. After some experimentation with the user cost equations, it was found that the effects of gradient on the maintenance resource costs are insignificant. Hence, the *GRAD* variable is included only in the fuel consumption equations and not in the other user-cost equations. The

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TABLE 13. Model 2-2, Structural Model: Functional Performance

Independent variable (1)	Estimate (2)	*t*-statistic (3)
AGER/SNC	4.443	16.56
ESAXL/SNC	0.434	1.05
CP/SNC	3.218	5.34

Note: Squared multiple correlation = 0.48.

TABLE 14. Model 2-2, Structural Model: Structural Performance

Independent variable (1)	Estimate (2)	*t*-statistic (3)
AGER/SNC	0.053	11.87
ESAXL/SNC	0.109	13.69
CP/SNC	0.000	0.21

Note: Squared multiple correlation = 0.42.

TABLE 15. Model 2-2, Structural Model: User Cost

Category of vehicle (1)	Dependent variable (2)	Functional performance (3)	Gradient (4)	Squared multiple correlation (5)
Cars and utilities	fuel consumption	0.481	24.85	0.96
	(liters)	(10.89)[a]	(202.19)[a]	—
	maintenance parts	6.89×10^{-6}	—	0.28
	(fraction of new vehicle)	(23.56)[a]	—	—
	maintenance labor	3.89×10^{-3}	—	0.26
	(hours)	(25.19)[a]	—	—
Buses and trucks	fuel consumption	−0.261	147.56	0.87
	(liters)	(−0.73)[a]	(90.67)[a]	—
	maintenance parts	1.99×10^{-4}	—	0.89
	(fraction of new vehicle)	(96.06)[a]	—	—
	maintenance labor	0.507	—	0.92
	(hours)	(92.98)[a]	—	—

[a]*t*-statistics in parentheses.

TABLE 16. Model 2-2, Measurement Model

Indicator (1)	Functional Performance		Structural Performance		Squared multiple correlation (6)
	Estimate (2)	*t*-statistic (3)	Estimate (4)	*t*-statistic (5)	
Roughness	1.000	—[a]	—	—	0.53
Cracking	1.289	18.23	—	—	0.36
Rut depth	—	—	9.341	16.98	0.80
Surface patching	0.315	12.76	—	—	0.16
Raveling	0.395	7.45	—	—	0.08
Benkelman deflection	—	—	1.000	—[a]	0.40

[a]Fixed parameters.

TABLE 17. Model 2-2, Extracted Performance Model

Indicator (1)	Functional Performance		Structural Performance	
	Estimate (2)	*t*-statistic (3)	Estimate (4)	*t*-statistic (5)
Roughness	0.393	67.21	—	—
Cracking	0.167	39.37	—	—
Rut depth	—	—	0.065	138.33
Surface patching	0.071	7.64	—	—
Raveling	0.098	13.56	—	—
Benkelman deflection	—	—	0.079	22.73
Squared multiple correlation	0.89		0.94	

Note: Total number of observations = 1,543.

structural model is given as follows.

Structural Model

$$S = \gamma_1 AGER/SNC + \gamma_2 ESAXL/SNC + \gamma_3 CP/SNC + \zeta_1 \quad (22)$$

$$FCCU = \alpha_1 S + \beta_1 GRAD + \zeta_2; \quad MPCU = \alpha_2 S + \zeta_3; \quad MLCU = \alpha_3 S + \zeta_4 \quad (23\text{–}25)$$

$$FCBT = \alpha_4 S + \beta_2 GRAD + \zeta_5; \quad MPBT = \alpha_5 S + \zeta_6; \quad MLBT = \alpha_6 S + \zeta_7 \quad (26\text{–}28)$$

The specification of the measurement model is the same as in Model 1-1.

The estimated structural model is presented in Tables 11 and 12. The fit of the deterioration model is 0.61 with all the estimated parameters significant. In the user-cost equations all of the estimated parameters have the expected signs except for the coefficient of latent performance in the fuel consumption equation for buses and trucks. But this coefficient is statistically insignificant implying that the condition of the pavement has negligible effect on the fuel consumption of buses and trucks. It must be noted that the corresponding coefficient for cars and utilities is statistically significant. Except for the maintenance costs equations for cars and utilities, all the user cost equations have good fits as seen in their relatively high SMCs.

The estimated measurement and extracted performance models are similar to those of Model 1-1, and hence these models not presented here.

Two-Component Latent Performance Model: Model 2-2. In this model, the structural equations for structural and functional performance latent variables, and the measurement model have the same form as in Model 1-2. But the user costs are split into the dominant components as in Model 2-1. The estimated structural model is presented in Tables 13–15, the measurement model in Table 16, and the extracted performance model in Table 17. All the parameters in the user-cost equations have the expected signs expect the coefficient of functional performance variable in the fuel consumption equation for buses and trucks. But this coefficient is insignificant too. The fits of all user-cost equations, especially maintenance parts and labor equations for cars and utilities, have improved compared to Model 2-1.

CONCLUSIONS

The case study reconfirms the efficacy of the Ben-Akiva and Ramaswamy framework wherein the performance of a highway pavement is characterized by a latent variable and the distress measurements like roughness, cracking, raveling, rutting, etc. are used as indicators of the underlying latent performance. By including structural number, a measure of the thickness and stiffness of the different pavement layers, in the structural deterioration model the effects of pavement strength on the deterioration process are captured.

The estimated simultaneous performance and user-cost models demonstrate the importance of modeling a two-component latent performance vector for the highway example. The primary motivation for modeling the functional and structural performance deterioration processes separately, stems from the use of these deterioration models in the context of pavement management system. Maintenance and rehabilitation activities are undertaken to preserve the surface quality and structural integrity of the pavement. These activities consist of surface maintenance (routine maintenance, resurfacing, etc.) and structural maintenance (reconstruction). Also, in the case of preventive maintenance actions, one needs to model the structural performance deterioration as the structural aspect is of no immediate concern to the users, whereas it is critical to the highway agency in order to avoid more expensive corrective measures in the future. Model 1-2 and Model 2-2 demonstrate the identification and effectiveness of two-dimensional latent performance vector models. An interesting observation is the improvement in the fit of the user-cost equations, in a two-dimensional latent performance case, when user cost is specified as a function of the functional performance, compared to fit of user-cost equations in a single latent performance case. This has important consequences in the selection of maintenance and rehabilitation actions, since different maintenance actions affect the user costs and agency costs differently. Further, this distinction helps in the identification of appropriate maintenance actions, if these actions are chosen to minimize both maintenance costs and user costs.

Further, comparing the estimated user cost equations for Model 2-1 and Model 2-2, the importance of estimating disaggregate user-cost components is observed as different user-cost components are affected by different performance and roadway characteristics. For example, fuel costs for cars and utilities depend on the functional performance of the pavement, while fuel costs for buses and trucks are largely unaffected by the functional performance. On the other hand, maintenance parts and labor costs for both vehicle categories depend on the functional performance. This has implications on the design of optimal maintenance and rehabilitation strategies.

The above observations suggest that the adoption of two-dimensional latent performance models with disaggregate user costs may provide useful inputs to pavement management. It must be reiterated that this paper presents a preliminary assessment of the potential for the new approach of modeling infrastructure performance and user costs jointly. Further empirical work is needed to substantiate the usefulness of our framework in other infrastructure settings, and from the perspective of its application to optimal selection of infrastructure maintenance and inspection strategies.

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APPENDIX I. BRIEF REVIEW OF LATENT VARIABLE MODELS

Latent variables are hypothetical constructs conceived by an analyst, and for which there exists no operational methods for direct measurement. Although latent variables are not observable, one can hypothesize that their effects on measurable variables are observable. In some cases, the observed variables, considered to be manifestations of the underlying latent variable (hence also manifest variables or indicators), will be discrete (nominal), in others continuous (interval or ratio) variables.

A latent variable model is used to estimate the value of a latent variable from observations of the indicators. Such a model consists essentially of two parts: a measurement model and a

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structural model. The first of these specifies how the latent variables are related to the observed or measured variables (i.e., indicators are manifestations of the underlying latent variables) and the second specifies the relationship among the latent variables.

The structural model relates two types of latent variables—dependent and explanatory—by a linear structural equation of the form

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{29}$$

where $\boldsymbol{\eta}$ = vector of latent endogenous random variables and is $m \times 1$; $\boldsymbol{\xi}$ = vector of latent exogenous random variables and is $n \times 1$; $\mathbf{B} = m \times m$ coefficient matrix showing the influence of the latent endogenous variables on each other; $\boldsymbol{\Gamma} = m \times n$ coefficient matrix for the effects of $\boldsymbol{\xi}$ on $\boldsymbol{\eta}$. The matrix $(\mathbf{I} - \mathbf{B})$ is assumed to be nonsingular. $\boldsymbol{\zeta}$ = an $m \times 1$ disturbance vector and is assumed to have an expected value of zero and to be uncorrelated with $\boldsymbol{\xi}$.

The measurement model can be written as

$$\mathbf{y} = \boldsymbol{\Lambda}_y\boldsymbol{\eta} + \boldsymbol{\varepsilon}; \qquad \mathbf{x} = \boldsymbol{\Lambda}_x\boldsymbol{\xi} + \boldsymbol{\delta} \tag{30, 31}$$

The $\mathbf{y}:(p \times 1)$ and $\mathbf{x}:(q \times 1)$ = observed variables; $\boldsymbol{\Lambda}_y:(p \times m)$ and $\boldsymbol{\Lambda}_x:(q \times n)$ = coefficient matrices that show the relation of $\mathbf{y}$ to $\boldsymbol{\eta}$ and $\mathbf{x}$ to $\boldsymbol{\xi}$, respectively; and $\boldsymbol{\varepsilon}:(p \times 1)$ and $\boldsymbol{\delta}:(q \times 1)$ = errors of measurement for $\mathbf{y}$ and $\mathbf{x}$, respectively. The errors of measurement are assumed to be uncorrelated with $\boldsymbol{\eta}$, $\boldsymbol{\xi}$, and $\boldsymbol{\zeta}$ and with each other. The expected values of $\boldsymbol{\varepsilon}$ and $\boldsymbol{\delta}$ are zero. To simplify matters $\mathbf{y}$ and $\mathbf{x}$ are written as deviations from their respective means (without any loss of generality).

The crucial assumption of latent variable models is that of conditional independence, which states that given the values of the latent variables, the manifest variables are independent of one another. The assumption of conditional independence implies that it is the latent variables which produce the observed relationships among the manifest variables. The observed interdependence among the manifest variables is due to their common dependence on the latent variables and that once these have been defined, the behavior of the manifest variables is essentially random.

Let the unknown parameters be stacked in a vector $\boldsymbol{\theta}$. S_{yy} represents the observed covariance matrix of the $\mathbf{y}$ variables, and S_{yx} the observed covariance between the $\mathbf{y}$ and $\mathbf{x}$ variables, and S_{xx} the covariance matrix of the $\mathbf{x}$ variables. Then the covariance matrix of the observed $[\mathbf{y}', \mathbf{x}']'$ is given by

$$\mathbf{S} = \begin{bmatrix} S_{yy} & S_{yx} \\ S_{xy} & S_{xx} \end{bmatrix} \tag{32}$$

Let $\Sigma\ (\boldsymbol{\theta})$ represent the covariance matrix of the vector $[\mathbf{y}', \mathbf{x}']'$ implied by the model system, i.e., as a function of the unknown parameter vector $\boldsymbol{\theta}$

$$\sum\ (\boldsymbol{\theta}) = \begin{bmatrix} \Sigma_{yy}\ (\boldsymbol{\theta}) & \Sigma_{yx}\ (\boldsymbol{\theta}) \\ \Sigma_{xy}\ (\boldsymbol{\theta}) & \Sigma_{xx}\ (\boldsymbol{\theta}) \end{bmatrix} \tag{33}$$

Estimation of the parameters is based on the idea of replicating the observed covariance matrix with the implied covariance matrix. The models imply a particular structure for the population covariance matrix for the observed variables, in the sense that the elements are given by particular functions of the parameters of the model. Let $\boldsymbol{\Theta}$ be the parameter space such that $\boldsymbol{\theta} \in \boldsymbol{\Theta}$. The parameter vector $\boldsymbol{\theta}$ is obtained by minimizing a fitting function $\mathcal{F}(\mathbf{S}, \Sigma\ (\boldsymbol{\theta}))$ over $\boldsymbol{\theta} \in \boldsymbol{\Theta}$ satisfying the conditions (Everitt 1984)

1. $\mathcal{F} \geq 0$
2. $\mathcal{F} = 0$ iff $\mathbf{S} = \Sigma\ (\boldsymbol{\theta})$
3. $\mathcal{F}$ is continuous over $\mathbf{S}$ and $\Sigma\ (\boldsymbol{\theta})$

A comprehensive treatment of the theory and estimation of latent variable model is found in Bollen (1989) and Everitt (1984). In our case, the explanatory variables are assumed to be directly observable without any measurement error, and (31) reduces to

$$\mathbf{x} = \boldsymbol{\xi} \tag{34}$$

Such a model system is referred to as a MIMIC (multiple indicators multiple causes) model.

Primarily two methods are adopted to extract the latent variables as a function of the indicators. If the extraction is based on the information from the indicator variables $\mathbf{y}$, then the extraction procedure is called the Partial Information Extraction Method. If the extraction is based on information from both the explanatory variables $\mathbf{x}$ and the indicator variables $\mathbf{y}$, then the extraction method is called the Full Information Extraction Method. The basic idea in the full information extraction method for the MIMIC model is to assume a multivariate normal distribution for $[\boldsymbol{\eta}', \mathbf{y}', \mathbf{x}']'$ and use the conditional distribution of $\boldsymbol{\eta}$ given $[\mathbf{y}', \mathbf{x}']'$ to fit the latent variables as functions of **y** and **x**. These fitted values are then regressed on the indicators **y** to obtain the coefficients of the extracted latent variable model [see Gopinath (1992) for a detailed presentation of the different extraction methods].

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APPENDIX III. NOTATION

The following symbols are used in this paper:

- $\mathbf{C}$ = user costs;
- $\mathbf{I}$ = vector of condition indicators;
- $\mathbf{S}$ = latent facility performance vector;
- $\mathbf{X}_1$ = vector of explanatory variables affecting facility performance;
- $\mathbf{X}_2$ = vector of explanatory variables affecting user cost;
- $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\Gamma}$ = unknown parameters in structural model;
- $\boldsymbol{\varepsilon}$ = error vector in measurement model;
- $\boldsymbol{\zeta}_1, \boldsymbol{\zeta}_2$ = error vectors in structural model; and
- $\boldsymbol{\Lambda}$ = unknown parameters in measurement model.

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