Latent Performance Approach to Infrastructure Management

MOSHE BEN-AKIVA, FRANNIE HUMPLICK, SAMER MADANAT, AND ROHIT RAMASWAMY

A new framework for the analysis of infrastructure performance and the planning of inspection and maintenance and rehabilitation (M&R) activities is described. The main facets of this framework are (a) treating facility performance, the key variable in the process, as a latent variable that manifests itself through measured condition indicators; (b) explicitly analyzing and including in the decision process the errors and uncertainties in infrastructure condition measurement and performance analysis; and (c) accounting for the interactions between the two decisions, inspection and maintenance strategies, by jointly selecting them within an optimization algorithm. A model system relating the latent facility performance to explanatory variables and to observed indicators is developed and parametric studies using this framework are presented. The approach recognizes the errors inherent in the measurement of the condition indicators; these errors are quantified through the use of measurement error models, which are estimated using a rigorous statistical method. The M&R activity planning model accounts for the presence of uncertainty in the output of the inspection of facility condition and the forecasting of facility performance. Inspection activity decisions are addressed jointly with the M&R activity decisions through a common stochastic optimization algorithm, which leads to the selection of cost-effective inspection activities. A parametric study investigating the effects of uncertainty in condition measurement and forecasting on life cycle costs is also presented.

The past decade has witnessed important developments in the area of infrastructure management: the application of a large number of automated data collection technologies such as photographic and video imaging, laser, radar and infrared nondestructive technologies (*1*). These developments have made available a large quantity of data for the analysis of infrastructure performance. On the other hand, existing approaches to performance modeling are based on indices calibrated using subjective ratings and a predetermined set of indicators that were selected at a time when less-developed data collection technologies (mainly visual inspection) were being used. Examples include the pavement serviceability index (PSI) (*2*) and the pavement condition index PCI (*3*). An improved performance modeling methodology is needed to exploit these enhanced data collection capabilities.

Before adapting a new data collection technology, its accuracy and precision must be analyzed. The results of such an analysis serve several purposes. First, they are inputs into cost-benefit evaluation of new infrastructure inspection technologies, with the aim of selecting among them. Second, knowledge of the precision of the measurements made by these technologies is a necessary input to the maintenance and rehabilitation (M&R) strategy selection process, to incorporate the risk element in decisions on the basis of these measurements. Finally, any algorithm determining the inspection frequencies for infrastructure facilities using these technologies must be based on the knowledge of their precisions.

The infrastructure management process can be divided into three main areas:

- Data collection and inspection,
- Performance modelling and forecasting, and
- Decision making for inspection and M&R.

These areas are related in the manner shown in Figure 1. The facility condition data collected using different inspection technologies are used in two ways: to estimate infrastructure performance models and to select maintenance and rehabilitation (M&R) strategies. Infrastructure performance models are used in planning present and future inspection and M&R activities. The decision-making block not only selects M&R activities, but also future inspection strategies and data collection procedures. This effect is represented by the feedback loop of Figure 1.

A methodological framework to support the infrastructure management process in Figure 1 is described. The main facets of this framework are

- Treating the key variable in the process, facility performance, as a latent variable that manifests itself through measured condition indicators;
- Explicitly analyzing and accounting for the errors and uncertainties in infrastructure condition measurement and performance analysis in the decision-making process; and
- Accounting for the interaction between the two decisions, inspection and maintenance strategies, by jointly selecting them within an optimization algorithm.

Figure 2 shows the methodological framework of this research. In this figure, rectangles represent observed quantities, ellipses represent latent variables, and diamonds represent decisions. At the upper level of the diagram, the true values of condition (or performance) indicators of an infrastructure facility are estimated from the indicator measurements obtained through different measurement technologies. The relationship between the two is explained by a measurement error model, and it is a function of technological, en-

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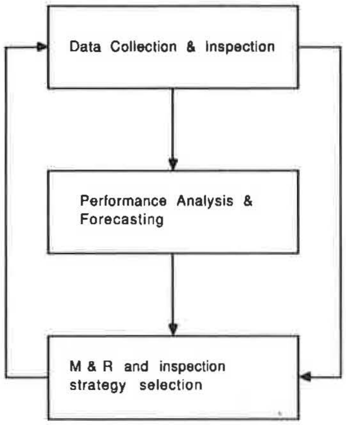

FIGURE 1 The infrastructure management process.

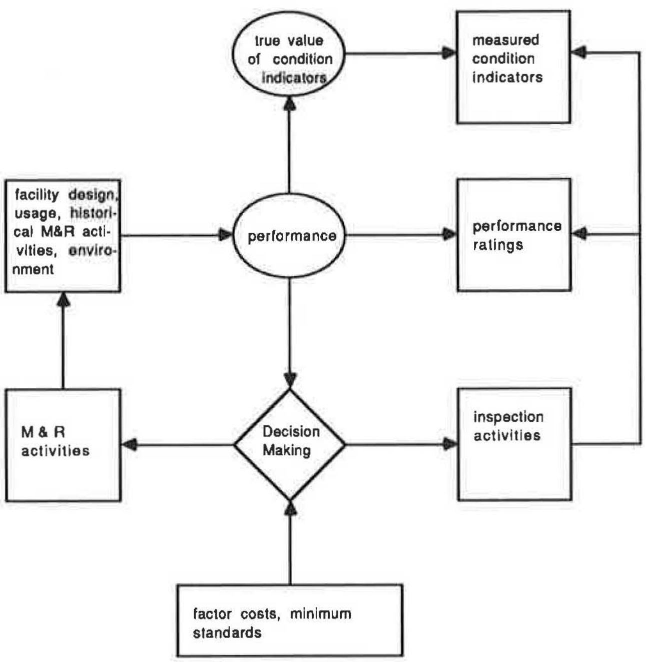

FIGURE 2 The latent performance theoretical framework.

vironmental, facility and damage-specific factors. The true values of condition indicators are an input in the second level, where the performance of a facility is estimated through a performance model. The other inputs to this model system are exogenous variables such as usage, environment, past maintenance and rehabilitation activities, facility characteristics, and possible performance ratings. This model system provides unbiased estimates of the present performance of an infrastructure facility, if the models are correctly specified, and can be used to forecast future performance. Both present and forecasted performance are inputs to the third level, in which inspection and M&R decisions are jointly made. Other inputs to the algorithm are the measurement error models estimated in the first level, the performance models estimated in the second level, the costs of different activities, and minimum performance standards. The outputs of the algorithm are optimum inspection and maintenance activities that feed back into the higher levels of the model.

Each of the three areas of the methodological framework for infrastructure management is described in the following sections. A parametric study demonstrating the framework developed and areas of further research are also discussed.

DATA COLLECTION

Infrastructure performance is characterized by a number of indicators, for example, cracking, rutting, potholes, and roughness, in the case of highway pavements. In order to measure these indicators, a range of inspection methods exist, ranging from manual to fully automated inspection. Technologies for surface inspection of distresses include photographic imaging, video imaging, and laser nondestructive measurement. The measurements by these technologies are subject to significant errors, which can be attributed to

1. Technological factors (e.g., resolution and field of view);
2. Distress factors (e.g., dimensions of distress); and
3. Section or location factors (e.g., pavement type).

Measures of the accuracy of inspection technologies are important for several reasons. First, they can serve as an aid for developing new measurement technologies. Second, they form the basis for selecting inspection strategies. Finally, they can be included in a future inspection strategy and M&R decision model, to take into account the effect of measurement uncertainty on strategy selection.

The present approach for quantifying measurement errors is based on measurement error models. These models are mathematical expressions that explain the difference between the true value of an indicator at a given location, and its measured value, in terms of systematic biases and a random error. A possible specification of a linear model is

$$d_{ij} = \alpha_j + \beta_j d_i^* + \varepsilon_{ij} \tag{1}$$

where

d_{ij} = measured value of a condition indicator on Section i by Technology j;
d_i^* = true value of a condition indicator on Section i;
α_j, β_j = additive and multiplicative systematic biases of Technology j; and
ε_{ij} = random error of measurement on Section i by Technology j, with zero mean and variance denoted by σ_j^2.

In order to use such a model, the values of α_j, β_j, and σ_j^2 need to be known. Ideally, these parameters would be statistically estimated using a sample of measurements by different technologies, for indicators for which the true values are known. In the case of infrastructure facilities, the problem is that it is either impossible or prohibitively expensive to measure true values of condition indicators. Hence, estimation of such models is only possible if an assumption is made that an unbiased reference measurement exists, such as from an unbiased average of multiple technologies. Such a measurement can be obtained if technologies with radically different measurement principles (such as combining measurements from a video imaging technology with those from a laser nondestructive measurement technology) are used in such a manner that the average bias of the measurements from these technologies is zero. Such averages were developed and tested by Humplick (*4*).

Given such a reference measurement, estimation of the model parameters can be achieved using the technique of factor analysis. This technique assumes that the true value of a condition indicator is latent and uses a sample of measurements, including the reference measurement, to estimate α_j, β_j and σ_j^2. The advantage of this approach over simple regression methods is that it produces unbiased estimates of the model parameters (*4*).

The approach was applied to a data set from an FHWA study, *Improved Methods and Equipment to Conduct Pavement Distress Surveys*, conducted in Texas (*1*). The study included measurement of surface distresses on highway pavements using a variety of existing and newly developed technologies and methods. The technologies included three direct measurement techniques (mapping, manual, and logging) involving visual inspection by humans; and four indirect measurement techniques involving optical imaging (photo1, photo2, and video) and a laser nondestructive measurement technique. The technologies used had a wide range of capabilities for resolution of measurement, sampling size, and data processing and reduction.

Examples of estimated models for measurements of the area of alligator cracking on pavement sections in the study by direct (manual) and indirect (photo1) measurement technologies, respectively, follow:

$$\hat{d}_{\text{manual}} = 132.2 + 0.39d^*,\ \hat{\sigma}_{\text{manual}} = 263 \text{ ft}^2,\ R^2 = 0.94$$

$$\hat{d}_{\text{photo1}} = 53.3 + 0.87d^*,\ \hat{\sigma}_{\text{photo1}} = 444 \text{ ft}^2,\ R^2 = 0.95$$

These models were estimated using factor analytic techniques that do not require knowledge of the true value for measurement bias estimation. The estimation procedure and the major assumptions required for estimation were provided by Humplick (*4*). The goodness of fit (R^2) obtained from such models is better than that obtained using traditional regression techniques (*4*).

Estimated models such as these can be used for correcting the results of inspection using the estimated values of α_j, and β_j, and for calculating confidence intervals around the corrected values using σ_j^2. They can also be used to select among available technologies, by comparing accuracies and precisions of a variety of technologies. For example, from the models presented, photo1 would be selected over manual on the basis of lower additive and multiplicative bias. However, assuming systematic biases could be corrected for given that they are known, manual would be selected over photo1 on the basis of lower random error of measurement. Alternatively, the mean squared error (MSE), which is a quantity combining the systematic bias and the variance of a measurement, could be used. Figure 3 shows plots of the MSE for the alternative technologies represented in the data set as a function of the true value of alligator cracking area. The true value of alligator cracking was extracted from the measured data using latent variable modeling techniques as discussed by Ben-Akiva and Humplick (*5*). The technology photo1 in Figure 3 lies below all the other technologies and hence has the lowest MSE. It is therefore dominant over all the other technologies from a combined bias and variance perspective.

In this research, measurement error models were estimated for seven different technologies, five types of condition indicators, and two pavement types. A more complete description of the work was given by Humplick (*4,6*). A further application of this methodology was provided by Livneh and Ben-Akiva (*7*).

PERFORMANCE MODELING

The scope of this part of the research is the estimation of an infrastructure deterioration model. Such a model relates the performance of an infrastructure facility to a set of causal variables such as traffic, age, and maintenance history. Such a model is required for planning maintenance and rehabilitation activities for infrastructure facilities.

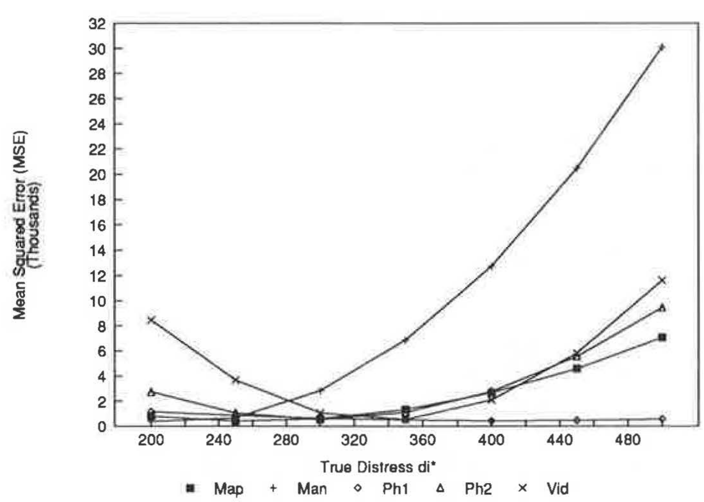

FIGURE 3 Mean square error for different measurement technologies used in alligator cracking.

The main problem in estimating such a model is that performance is not directly observable. What can be observed are indicators of performance, such as roughness, cracking, rutting, and skid resistance, as was discussed earlier.

Numerous studies have attempted to devise performance indices that combine different indicators into a single quantity, for example, pavement condition index (PCI) and present serviceability index (PSI). These indices were based on the subjective judgment of pavement experts. They lack rigorous justification, have poor explanatory power, and use a predetermined set of indicators that precludes incorporation of new condition indicators. Furthermore, when these indices were used together with common causal variables to estimate a deterioration model, the resulting fit to data was poor.

On the other hand, the present approach does not rely on subjective judgment for devising a performance index. Indeed, it does not require the predetermination of such an index. Instead, it treats performance as a latent variable S that is linked to explanatory (or causal) variables (X) and maintenance actions (A) through a deterioration model. Moreover, it is linked to a set of condition indicators (D) through a measurement model. These models form a system of equations that are estimated simultaneously, thereby producing a much better fit to data than traditional deterioration models. Figure 4 shows a schematic representation of the process. In this figure, rectangles represent observed quantities, whereas the ellipse represents the unobserved latent performance.

This approach was applied to a data set consisting of 3,837 1-mi pavement sections from Nevada. This set contained information on several condition indicators (such as cracking, rut depth, and roughness) for each section, as well as a set of causal variables (average daily traffic, percent truck traffic, age, maintenance by several activities, and several environmental variables).

In the process of estimating the model system, a major problem was uncovered that had not been resolved in existing deterioration models that are estimated with data from in-service pavements. Such pavements are subjected to maintenance performed by highway agencies in response to their level of traffic, percentage of trucks, etc. As a result, pavements with the highest level of usage will receive higher levels of maintenance. In other words, two conflicting mechanisms are acting on these pavements:

1. A deterioration mechanism, because of which condition decreases as traffic and age increase; and
2. A maintenance mechanism, because of which condition increases as traffic increases.

An attempt to estimate a deterioration model from in-service pavements without taking the second mechanism into account, as is usually the case with state-of-the-art deterioration models, will result in biased, counterintuitive parameter estimates. The correct specification for such a situation is a simultaneous equation model, including two separate relationships, one for each of the two mechanisms described earlier.

Several examples of an estimated deterioration equation of a latent variable model system have been provided (*8–10*). The results indicate that all the parameter estimates have intuitively correct signs. This result follows from the simultaneous equation specification. The value of R^2, which is a measure of fit to data, is also reported and is higher than is usually the case in existing deterioration models. It follows from using the latent variable approach. A complete description of work in this area is also provided in the references.

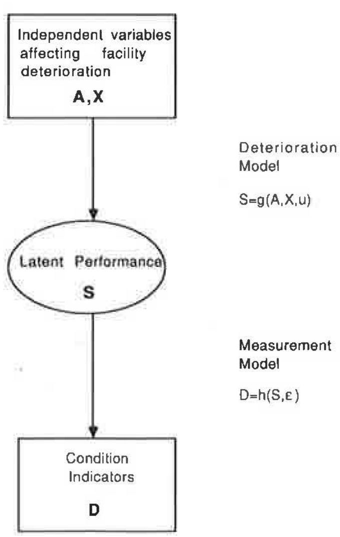

FIGURE 4 An integrated model of latent facility performance and condition measurement.

DECISION MAKING

In the process of managing their systems of facilities, infrastructure agencies are faced with decisions. For example, to which facilities should an M&R activity be applied in a given year? These decisions are complicated by the difficulty in accurately predicting the future performance of infrastructure facilities because of the uncertainty in the deterioration process and in the effects of various M&R activities.

Several research efforts to develop a rigorous systematic decision-making process (commonly using operations research techniques) to address these decisions have been made in the last decade. However, most of these have ignored the inherent uncertainty in measuring and forecasting facility performance, which have made them of little use when applied in the field. Exceptions to this trend (*11,12*) adopted a stochastic optimization approach to account for the uncertainty in predicted performance. However, this approach assumes that there is no uncertainty in the measured facility condition. Because infrastructure management requires a combination of inspection and prediction of facility performance, and because the uncertainty in inspection is not negligible (as demonstrated in the research on measurement errors), there is a need to develop a methodology that takes into account both sources of uncertainty.

On the other hand, infrastructure agencies also need to make decisions regarding the frequency of their inspections and the technologies to use during these inspections. Traditionally, such decisions have been made with no explicit cost-effectiveness considerations, such as the penalty for delayed detection of deterioration. A methodology that recognizes the potential trade-offs between inspection costs and the added costs of M&R is required to address the inspection decisions in a systematic manner. As an example of this trade-off, increasing the frequency of inspections increases the inspection costs but enhances the quality of information available to the decision maker, which allows for better M&R decisions, hence reducing life cycle M&R costs.

The proposed methodology addresses both these concerns. It recognizes the uncertainty in both facility condition prediction and measurement, and it is based on the minimization of the sum of expected M&R and inspection costs. The first issue is addressed through the use of the latent Markov decision process (LMDP). The LMDP is an extension of the traditional Markov decision process (MDP) methodology, but differs from it in one major aspect: it does not assume the measurement of facility condition to be necessarily error-free. Instead, it recognizes that the decision maker observes outputs from measurement (such as results of inspection using the technologies discussed earlier), which are probabilistically related to the true condition of the facility. This methodology was developed in the field of manufacturing (*13*), and is often referred to as a partially observable Markov decision process (POMDP).

In order to select M&R policies in a meaningful manner when there is measurement uncertainty, the decision maker cannot make decisions only on the basis of the measured condition of the facility. Instead, all the information available to the decision maker about the facility (the history of measured condition states and M&R activities) can be relevant to future decisions. This history is referred to as "the state of the information." It can be shown that if the deterioration of the facility is represented by a finite-state Markov chain and the measurement uncertainty is represented by a set of discrete probabilities, then the state of the information itself will evolve in a Markovian fashion (*14*). Hence, the M&R decision problem is transformed from a problem of a latent state (the condition state of the facility) to one of an observed state (the state of information for the facility). Once this transformation has been performed, the same solution method (namely dynamic programming) that is used to find optimal M&R policies by minimizing expected costs for an MDP can be adapted to the LMDP.

The similarity between the LMDP and the classical MDP can be best explained in terms of the underlying decision trees. Figure 5 shows a classical MDP tree. At the beginning of time Period t, the true state x_t is observed. On the basis of this knowledge, the decision maker selects an activity a_t. Given the condition state x_t, and the selected activity a_t, the facility moves to one of the states $x_{t+1} = j$ with probability $P(x_{t+1} = j|x_t, a_t)$. The same process is then repeated in time Period $t + 1$, and so on.

In Figure 6, part of an LMDP tree is shown. The process starts in Period t, when the decision maker has available the state of information I_t. On the basis of this information, an activity a_t is selected. Given the information state I_t and a_t, the system moves to one of the states $I_{t+1} = K$ with probability $P(I_{t+1} = K|I_t, a_t)$. The same process is then repeated in time Period $t + 1$, and so on.

The second issue is addressed by making the decision of when to inspect jointly with the M&R decisions. The basis

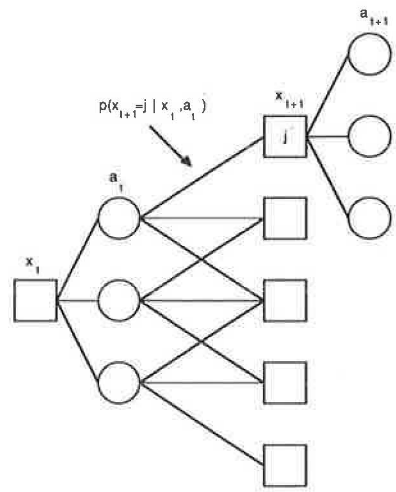

FIGURE 5 Decision tree for the MDP.

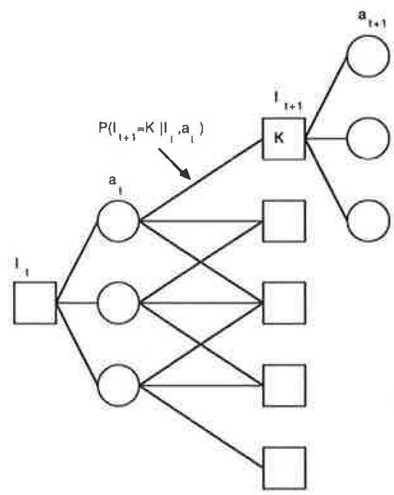

FIGURE 6 Decision tree for the LMDP with annual inspections.

for this approach is that an M&R decision can be made without being preceded by an inspection if the information revealed by the latter does not improve on the quality of the former. An inspection is only performed if the reduction in life cycle costs, achieved by selecting a different M&R activity as a result of the added information provided by this inspection, offsets the cost of inspection. This idea allows the agency to jointly optimize expected inspection and M&R costs, thus achieving lower costs than are possible by addressing each decision separately. This joint optimization is performed within the LMDP framework, leading to a model that is referred to as the LMDP with "unconstrained inspection frequency."

The inputs to this decision-making algorithm are

1. Estimates of the uncertainties associated with the measurements obtained from inspection technologies, which were obtained in the first part of this research,
2. Facility performance models, and their uncertainties, which were estimated in the second part of this research,

3. Agency costs, for the different maintenance, rehabilitation, and inspection activities; and
4. Minimum performance standards, which were required in this model because of the lack of realistic user cost models. When available, user cost models can be readily incorporated in the optimization in place of the minimum standards.

The outputs from the measurement error models and the performance models estimated in the first two parts of this research are discretized before being used in the decision-making algorithm, because the latter operates on a discrete facility performance state space.

The algorithm provides the decision-making agency with the following outputs: (a) optimal maintenance and rehabilitation policies for all the years of the planning horizon; (b) optimal inspection policies (whether to inspect or not), for all the years of the planning horizon; (c) minimum total expected cost of inspecting and maintaining the facility for the duration of the planning horizon, for the optimal policies; and (d) other statistics of interest, such as the expected number of inspections for the facility for the duration of the planning horizon, for the optimal policies.

PARAMETRIC STUDY

This new approach, beyond being a tool for selecting M&R and inspection strategies, can serve as a means for quantifying the expected benefits from using more precise, and more expensive, measurement technologies. To investigate the value of these expected benefits, a parametric study was performed, in which the precision of the measurement technologies used (as given by the standard deviation of the measurement) were varied, while the inspection frequency was constrained to once a year, and the minimum expected life cycle costs obtained by the algorithm were plotted.

The study indicated that the expected life cycle cost increased monotonically with decreasing forecasting precision of the performance model used. This is shown in Figure 7, in which the horizontal axis represents the standard deviation of measurement, the vertical axis represents the minimum expected lifecycle costs, and different curves represent different forecasting precisions of the performance model. [The inverse of precision is used, as given by the standard error of the forecast, s.e.(S).] The study also indicated that there exists an optimum value for the precision of the measurement technologies, as shown in Figure 7. For precisions above this optimum value, the minimum total expected costs increased because of the increase in the costs of inspection, using an increasingly precise and expensive technology. For precisions below this optimum value, the minimum expected total costs increased due to the increase in the expected M&R costs, due to the uncertainty in the output of the measurement technology. This trend is more pronounced for low precisions of the performance model [s.e.(S) $>$ 0.4 in Figure 7]. When the performance model forecast becomes more precise, inspections provide less new information, so that their contribution to reducing total cost is limited, as can be seen in the lower curves of Figure 7. At the extreme, where the performance model forecasts contain almost no uncertainty (the lowest curve in Figure 7), increased inspection precision does not provide any information at all, so that increased precision only leads to an increase in inspection costs without reducing M&R costs. This is why, if the forecast is perfect and if inspections are to be performed annually, the optimal inspection technology is the one that is the least precise.

The same parametric study was repeated, this time without constraining the inspection frequency to once a year. In Figure 8, the minimum expected life cycle costs are shown as functions of the standard deviation of measurement, with different curves representing different precisions of the performance forecasting model. The shape of the curves shown here is somewhat different than in the constrained case.

In the case when the performance forecast contains no uncertainty [s.e.(S) = 0.2], the curve is flat, which means that the minimum expected life cycle costs are independent of the measurement uncertainty. The reason for this is clear: because there is no uncertainty in performance forecasting, inspections cannot contribute to reducing expected costs, so it is optimal not to inspect. This can be verified by examining Figure 9,

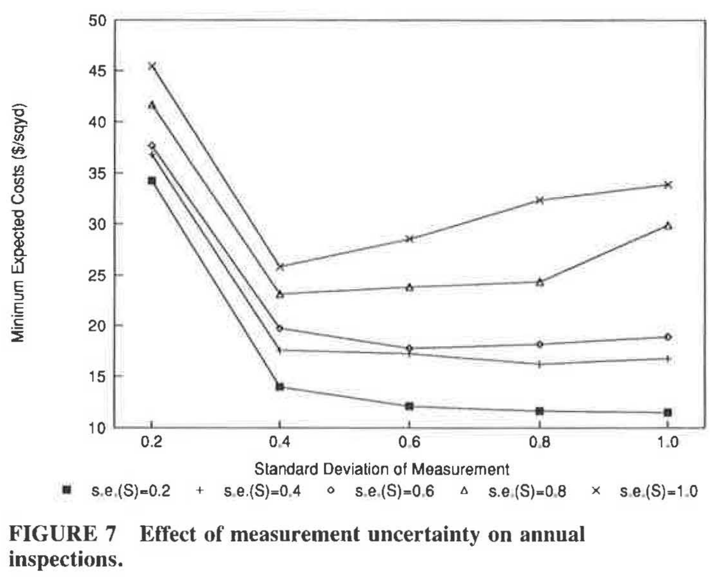

FIGURE 7 Effect of measurement uncertainty on annual inspections.

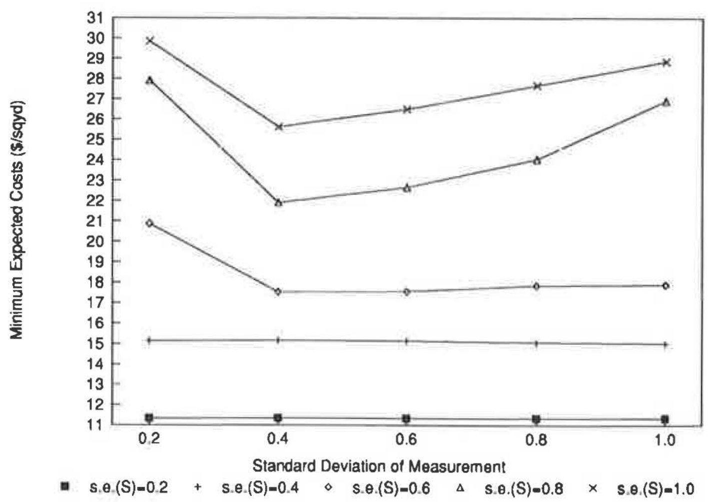

FIGURE 8 Effect of measurement uncertainty on optimal inspection frequency.

which shows the expected number of inspections for the 10-year horizon (using the optimal policy) as a function of the standard deviation of measurement. The first curve of this figure indicates that the optimum expected number of inspections, when s.e.(S) = 0.2, is zero. As the standard deviation of forecasting increases, so does the need for inspections. This result is shown in Figure 9, in which for a given measurement technology, the number of inspections increases as the precision of the forecast of the performance model decreases.

For a given forecasting precision, the benefits of inspection have to be traded off against the cost of inspection. When the costs, and precision, are excessively high, as for the measurement technology shown at the left in Figure 9, the costs of inspecting offset the benefits brought about by reduced uncertainty. Towards the right in Figure 9, the optimal number of inspections increases as the measurement precision decreases, until a point, after which it decreases. This variation in inspection frequency with decreasing inspection cost can be explained intuitively: initially, the cost of a single inspection decreases faster than its precision (and than the value of the information it provides) so it becomes optimal to inspect more often. However, after some point the precision of the measurement decreases faster than its unit cost, so that the information revealed by each inspection no longer justifies the cost, so it becomes optimal to inspect less.

The results of such a study can be used as part of a cost-benefit evaluation of new inspection technologies with known precisions. The reduction in expected life cycle costs resulting from using more precise measurement technologies, which are calculated in this study, can be compared to the fixed costs of acquiring these precise inspection technologies. A more detailed description of the work in this area was provided by Madanat (*14*).

FURTHER RESEARCH

Several refinements on these methodologies are possible. Some of them are

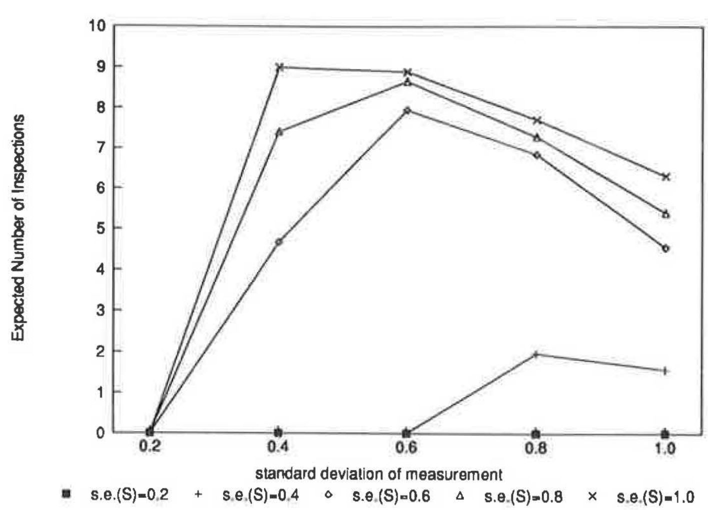

FIGURE 9 Effect of measurement uncertainty on expected number of inspections.

1. Incorporation of the severity dimension into the analysis of measurement errors. The measurement error models presented earlier did not investigate the effects of severity on the measurement biases and variances in different situations, because this information was not available in the data used in the study.

2. Linking the latent performance variable to different measures of user costs. This process will allow including user costs in the cost minimization algorithm of the decision-making model, instead of relying on minimum performance standards, as is the case now. This can be achieved by estimating a system of user cost equations simultaneously with the performance model system described earlier. Such an effort is currently in progress at Massachusetts Institute of Technology.

3. Extending the joint decision-making algorithm to handle network-level considerations, such as a budget constraint. Possible approaches for this extension are currently being evaluated.

CONCLUSIONS

A new framework for the analysis of infrastructure performance and a new approach for M&R decision making were described. The framework, which is based on the concept of latent performance, recognizes the fact that performance is a latent variable that cannot be measured directly. Instead, what can be measured are different performance indicators that are probabilistically related to it. These indicators are, in turn, measured with error, and their true value is also latent. Models for relating the measured value of performance indicators to their true value, and the true value to the underlying latent performance, have been developed in this research. In addition to these measurement models, a structural model relating latent performance to a number of exogenous variables, such as usage and environment, has been estimated.

These models serve as inputs to a decision-making algorithm. This algorithm specifies optimum M&R and inspection policies, taking into account the uncertainty inherent in the input models. As a result, the specified policies represent the best compromise between optimality and risk in decision making. Furthermore, this approach represents the first use of cost-effective approaches in making inspection decisions in the area of infrastructure management. Finally, this approach can be used as a decision aid in selecting among different inspection technologies.

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