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Uncertainty and Accuracy in Infrastructure Management and Repairs

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Abstract – We review the application of time series techniques in improving infrastructure maintenance and repair decisions especially when there is an issue with uncertainty and measurement error. The rationale for this research is formulated in general concern for enhancing the decision-making process related to the management of important assets, as the lack of sufficient information can lead to issues and further costs. Using historical performance data and the records of the repairs made in the past, time series models were used in identifying deterioration trends and assessing the impact of the existing management measures. Stochastic characteristics were employed in order to account for the uncertainties and variability that are associated with the model to provide accurate and realistic forecasts. These findings indicate that integrating time series analysis with the uncertainty assessment increases the reliability of lifespan estimates for parts or the entire structure. It also provided an identification of ideal points for intervention that led to the reduction of unpredictable failures by 20% and the reduction of maintenance costs by 15% during five years. Furthermore, the model revealed the potential of enhancing the service life of infrastructures by up to 25% in terms of repair and maintenance schedules, which would provide a more effective management paradigm for infrastructures in the long run.

Keywords – Transport Infrastructure Life-Cycle, Infrastructure Management, Time Series Analysis, Markov Decision Processes, Maintenance and Repair.

I. INTRODUCTION

Transportation infrastructure life-cycle management is systematic approach of creating maintenance decisions for diverse transportation assets such as trains, bridges, and pavement [1, 2]. The transportation infrastructure systems in industrialized nations are well-established and experience significant deterioration of their components as a result of prolonged use [3]. The implementation of effective maintenance strategies for transportation facilities is crucial in order to enhance their state, since the economic and social operations of a nation are significantly dependent on effective transportation infrastructure [4]. Furthermore, the catastrophic consequences of transportation infrastructure collapse would include extensive property damage and significant loss of life. Multiple approaches, including optimum control, have been used to distribute finite resources across many time periods for the upkeep of transportation infrastructure [5, 6, 7]. The majority of these approaches provide comprehensive schedules, which include maintenance activities for each facility for each time interval.

In consistence with the timely review status of infrastructure control, discrete-time M&R optimization systems are often defined as a finite (action and state) Markov Decision Process (MDP) [8], with few exceptions. The optimum decision rule $\delta^* = (\delta_0^T, \dots \delta_T^T)$ for finite-horizon situations ($T < \infty$) may be calculated using backward induction, beginning at the terminal period, T. The ideal choice at time t may be influenced by both the present state s_t and the whole past history of the process, $d_t = \delta_t^T(s_t, H_{t-1})$, where $H_t = (s_0, d_0, \dots, s_{t-1}, d_{t-1})$. Nevertheless, when performing the backward induction process, it becomes evident that the Markovian structure of p and the additive separability of U suggest that it is superfluous to maintain a record of the complete past history. The optimal decision rule is solely determined by the present time t and the current state s_t, stated as $d_t = \delta_t^T(s_t)$. For instance, starting from time T, we get Eq. (1).

$$\delta_T(H_{T-1}, s_T) = \underset{d_T \epsilon D_T(s_T)}{\text{argmax}} \; U(H_{T-1}, s_T, d_T) \tag{1}$$

$$U(H_{T-1}, s_T, d_T) = \sum_{t=0}^{T} \left(\sum_{j=0}^{t-1} \beta_j(s_j, d_j)\right) u_t(s_t, d_t) \tag{2}$$

$$= \sum_{t=0}^{T-1} \left(\prod_{j=0}^{t-1} \beta_j(s_j, d_j)\right) u_t(s_t, d_t) + \left(\prod_{j=0}^{T-1} \beta_j(s_j, d_j)\right) u_T(s_T, d_T) \tag{3}$$

Based on Eq. (2), it is evident that the prior history H_{T-1} does not impact the optimum choice of d_T in Eq. (1) as d_T is only present in the last term $u_T(s_T, d_T)$ on the bottom part of Eq. (2). Considering that the last term is influenced only by the multiplicative discount factor $\prod_{j=0}^{T-1} B_j(S_j, d_j)$, it is evident that δ_T is solely dependent on s_T. By iteratively working backwards, it is directly possible to confirm that the optimum decision rule δ_t is dependent only on s_t at each time t. A Markovian decision rule is a mechanism that relies only on the present state s_t to determine the prior history of the process.

A fundamental hypothesis in MDP paradigm is that the state variables, which describe the status of a facility or proxies, are discrete. It is this apparently harmless hypothesis, which determine a significant discrepancy in the literature on infrastructure management. One aspect is the creation and refinement of statistical models for predicting conditions [10]. The idea of forecasting is founded on the assumption that historical and present information might be employed to provide recommendations on anticipated future events. In the context of time series analysis, there exists a prevailing notion that it is feasible to detect patterns within the past figures and efficiently employ them in the prediction of future values [11]. However, it is not predicted that futures values would be accurately predicted. Alternative forecasting methods for a single time series at a future time period include an anticipated value (referred to as a point prediction), a percentile, a perfection interval, and full prediction supply. This comprehensive collection of findings may be regarded as "the forecast" [12]. There are many more possible results of a forecasting procedure. In the context of anticipating an event, such as tool breakdown, time series data may have a limited effect on the prediction process. In practical applications, forecasting processes are most effective when they are directly relevant to the issue that has to be addressed [13, 14]. Thus, the theory may be formulated by comprehending the fundamental characteristics of the issue. Consequently, the theoretical findings might result in enhanced practical application.

The estimation and development of transition forecasts for performance prediction are conducted in accordance with the MDP framework. In this framework, conditions or their proxies are signified by variables illustrated over ordinal (and discrete) sets [15], [16], and [17]. The temporal series variability in this extended period, as defined by $Y_{max} – Y_{min}$ (the highest and lowest values of the variable measured during this interval), may be of considerable magnitude. If the range of variation is extensive, the local changes seen in a single candle will be somewhat little. Determining the appropriate method to discretize a wide range of variability presents a difficulty. By partitioning the range into a limited number of portions, known as states in the Markov model, the likelihood of a state changing will be greatly reduced [18]. The identification of this alternative state is, ultimately, an objective of prediction. If, conversely, the range of variability is partitioned into a substantial number of states, the concentration of occurrences per state will be reduced. This may not be enough to accurately determine the true distribution of the likelihood of state transitions [19]. The present problem will be resolved by the use of an innovative methodology that is absent in the aforementioned literature focused on Markov models.

The purpose of this study is to construct, and empirically test, a time series-based model that will help to improve the infrastructure stock management and repair decisions with the uncertainty consideration and different levels of measurement errors. The goal of the study is to develop prediction models that will allow the precise prediction of the rates of infrastructure degradation, determination of the most optimal time for maintenance, and the subsequent minimization of both random failures and overall maintenance costs, thereby contributing to better management of essential infrastructure systems. The remaining sections of this article have been organized in the following manner: Section II describe the model notation and assumptions. Data and methods, which also describe the deterioration model, measurement error model, and Kalman filter implementation, have been discussed in Section III. Section IV provides a detailed account of the findings, which describe the effects of uncertainty on optimal costs, systematic measurement error on life-cycle expenditures, and integrating various technologies for condition evaluation. Lastly, Section V summarizes these findings, and provides future scope for the research.

II. MODEL NOTATION AND ASSUMPTIONS

In this section, we provide the model as a substitute for the latent MDP formulation developed by Wang [20] to facilitate repair and maintenance decision-making for transportation infrastructures. An inherent challenge in incorporating measurements uncertainties into the MDP issue is that it contradicts the fundamental premise of having condition state knowledge after inspection. The initial state seen by the decision maker at time t is now an assessed state that is only probabilistically associated with the actual system state. The mathematical expression for this function is given by Eq. (3).

$$q(\hat{x}_t = k | x_t = j); 1 \leq j, k \leq n \;\; t = 0,1, \dots T \tag{4}$$

where $\hat{x}_t$ is the assessed condition status of the facility at t, x_t is the actual condition status of the facility at t, and j, k is the values of a discrete condition state, and q is an identified probability mass function. One approach to tackle the issue arising from the breach of the hypothesis of flawless assessment in augmentation states [21]. State augmentation refers to the process of redefining the current condition of system in any particular moment to integrate all the pertinent date accessible to the decision makers for future choices [22]. When the assessment of the facility's condition states is conducted with uncertainty, the decision maker has access to the whole record of measured states up to t, as well as the actions taken up to $t-1$. In addition, because the assessed state at t is only statistically associated with the real state at t, decision making cannot be adequately based just on knowledge of the measured state. Consequently, all the past recorded states and historical judgments may be applicable to future decisions and should be integrated into the enhanced state. To identify a new state using I_t, Eq. (4) and (5) emerge.

$$I_t = \{I_0, a_0, \hat{x}_1, a_1, \dots \hat{x}_{t-1}, a_{t-1}, \hat{x}_t\}; \;\; t = 1,2, \dots T \tag{5}$$

$$I_0 = \{\hat{x}_{-T}, a_{-T}, \dots \hat{x}_{-1}, a_{-1}, \hat{x}_0\} \tag{6}$$

where τ refers to the years between the initial facility inspection and the beginning of planning horizons. This follows Eq. (6), from which Eq. (7) can be obtained;

$$I_t = \{I_{t-1}, a_{t-1}, \hat{x}_t\}; \;\; t = 1, \dots, T \tag{7}$$

$$\rho(I_0|I_0, a_0, \hat{x}_1, I_1, \dots I_{t-2}, a_{t-2}, \hat{x}_{t-1}, I_{t-1}a_{t-1}) = P(I_t|I_{t-1}, a_{t-1}) \;\; t = 1, \dots, T \tag{8}$$

Given a given value of I_0, the transition probabilities $P(I_t|I_{t-1}, a_{t-1})$ determine the progression of the information state. This progression is Markovian, as shown by Eq. (7). Hence, we may formulate a dynamic design model over information state spaces. To simplify the notation, we will use the generic cost function $g(x_t, a_t)$). For that purpose, it is necessary to rephrase the cost function using the newly introduced variables. The Eq. (8) is used to determine the costs per phase as a functionality of the novel state, I_t, and activity a_t.

$$\bar{g}(I_t, a_t) = \underset{x_t}{\mathrm{E}}\{g(x_t, a_t|I_t)\} \tag{9}$$

where $\underset{x_t}{\mathrm{E}}\{g|I_t\}$ refers to the conditional projection of g over x_t, with condition I_t. The dynamic design modeling is provided by Eq. (9) and (10).

$$J_T(I_T) = \underset{x_t}{\mathrm{E}}\{gx_T|I_T\} \tag{10}$$

$$J_T(I_T) = \min_{a_t}\left(\underset{x_t}{\mathrm{E}}\{gx_T|I_T\} + \alpha \textstyle\sum_{.\forall L_{t+1}} \rho(I_{t+1} = L_{t+1}|I_t, a_t) J_{t+1}(L_{t+1})\right) \qquad t = 0, \dots, T-1 \tag{11}$$

where α refer to an annual discount amount factor, $\rho(I_{t+1} = L_{t+1}|I_t, a_t)$ = transition probabilities for the state of information, L_{t+1} = $\{I_t, a_t, \hat{x}_{t+1}\}$, and $\hat{x}_{t+1}$ = measured condition state at $t+1$. A prerequisite for solving Eq. (10), it is necessary to demonstrate the correlation between I_t and the probability distribution of x_t. Stated differently, we need knowledge of $p_t(x_t|I_t), \forall x_t, \forall x_t, \forall_t$, or, in vector form, $P_t|I_t, \forall I_t, \forall_t$, where $P_t|I_t$ is a vector of dimensions n, representing the information vector, with components $p_t(x_t|I_t)$. If we postulate that $P_0|I_0$ is known, then $P_t|I_t$ may be computed iteratively for all values of r, starting at t = 1, by employing Bayes' rule, that identified measurement probability, and transition probability. Let I_t be defined as the set of elements $\{I_{t-1}, a_{t-1}, \hat{x}_t\}$. Each element of $P_t|I_t$ may be represented by Eq. (11).

$$\rho_t(x_t = j|I_t) = \frac{prob(x_t + J, I_{t-1}, a_{t-1}\hat{x}_t)}{prob(I_{t-1}, a_{t-1}\hat{x}_t)} \tag{12}$$

$$= \frac{prob(x_t + J, \hat{x}_t \, I_{t-1}, a_{t-1})}{prob(\hat{x}_t|I_{t-1}, a_{t-1})} \tag{13}$$

$$= \frac{q(\hat{x}_t|x_t = j)\sum_i p(x_t = j|x_{t-1} = i, a_{t-1})\rho_{t-1}(x_{t-1} = i|I_{t-1})}{\sum_j q(\hat{x}_t|x_t = j)\sum_i p(x_t = j|x_{t-1} = i, a_{t-1})\rho_{t-1}(x_{t-1} = i|I_{t-1})}, j = 1, \dots, n \tag{14}$$

Using the elements $\rho_t(x_t = i|I_t)$ calculate above, (11) can be written as Eq. (12).

$$J_T(I_T) = \textstyle\sum_{i=1}^{n} \rho_T(x_T = i|I_T) g(x_T); \;\; \forall I - \tag{15}$$

$$J_t(I_T) = \min_{a_i}(\textstyle\sum_{i=1}^{n} \rho_t(x_t = i|I_t) g(x_t, a_t) + \alpha \sum_{k=1}^{n} \rho(\hat{x}_{t+1} = k|I_t, a_t) J_{t+1}(I_t, a_t, \hat{x}_{t+1} = k)) \;\; \forall I_t \;\; t = 0, \dots T-1 \tag{16}$$

The expression $P(\hat{x}_{t+1} = k|I_t, a_t)$ could be disintegrated into identifiable quantities, in Eq. (13).

$$\rho(\hat{x}_{t+1} = k|I_t, a_t) = \textstyle\sum_{j=1}^{n} q(\hat{x}_{t+1} = k|x_{t+1} = j) \sum_{i=1}^{n} \rho(x_{t+1} = j|x_t = i, a_t)\, \rho_t(x_t = i|I_t) \tag{17}$$

Substituting in (12), we get Eq. (14).

$$J_T(I_T) = \textstyle\sum_{i=1}^{n} \rho_T(x_T = i|I_T) g(x_T) \qquad \forall I_T \tag{18}$$

And (15).

$$J_t(I_t) = \min_{a_t}\big(\textstyle\sum_{i=1}^{n} \rho_t(x_t = i|I_t) g(x_t, a_t) + \alpha \sum_{i=1}^{n} \rho_t(x_t = i\big|I_t) \sum_{j=1}^{n} \rho(x_{t+1} = j\,|x_t = i, a_t) \sum_{k=1}^{n} q(\hat{x}_{t+1} = k|x_{t+1} = j) J_{t+1}(I_t, a_t, \hat{x}_{t+1} = k)\big) \tag{19}$$

$$\forall I_t, \quad t = 0, \dots, T-1 \tag{20}$$

The presented formulation could be represented as Latent Markov Decision Process (LMDP) with yearly inspections. This designation is based on the assumption that the facility state is latent and that facility state measurement $\hat{x}_t$ is accessible at the beginning of each year or time, t. The LMDP and the traditional MDP have a key resemblance that may be most effectively elucidated by examining the fundamental decision trees involved. Daoui, Abbad, and Tkiouat [23] elaborate on a traditional Markov Decision Process (MDP) tree. The real condition x_t is noticed at the start of time period t. Equipped with this information, the decision makers select actions a_t. In accordance to the finite condition x_t and the chosen activity a_t, facility transitions to a state $x_{t+1} = j$ having a probability $P(x_{t+1} = j|x_t, a_t)$. The same procedure is thereafter iterated in time period $t + 1$, and so on. An LMDP tree is given in [24]. The Hollins, Zilberstein, and Mouaddib [25] model begins at t, whenever a decision-maker has access to the current condition of data I_t. Considering this data, an activity is chosen. If the data state I_t and a_t are known, the system transitions to one of the states $I_{t+1} = K$ with a probability $P(I_{t+1} = K|I_t, a_t)$. The identical procedure is thereafter iterated in time period $t + 1$, and so on.

III. DATA AND METHODS

Data Sources

The data utilized in this study are derived from previous research on pavement distress assessment, specifically focusing on alligator cracking as recorded in the studies by El-Badawy, Jeong, and El-Basyouny [26]. These studies, provided a rich dataset on the performance of different inspection technologies used to assess the condition of in-service pavements. The numerical examples in this research rely on simulated data that closely mirror the measurement conditions and parameters described in these seminal studies. The true values of distress, expressed in square feet, vary between 200 and 500, reflecting the range of pavement deterioration observed in practice.

The initial condition of the facility, denoted as X_1, is set at 350.5 square feet, which corresponds to the optimal long-term steady state under the assumptions of the deterioration model employed in this study. The choice of X_1 is crucial, as it represents the starting point for all subsequent deterioration and maintenance simulations over the 100-period planning horizon. Additionally, economic parameters such as the discount rate are crucial for evaluating the present value of future costs. The discount rate is set constant at 5 percent ($\delta = \frac{1}{1.05}$) as has been used in other studies in the management of infrastructure and to capture the time value of money. The salvage value of the facility at the end of the planning horizon is assumed to be zero in line with traditional life cycle cost analysis where the goal is to control the state of the facility at the end of the planning horizon.

The choice of these data and parameters is made to make the simulation as realistic as possible and relevant to further infrastructure management. The results from the simulation and measurements yield an environment where effects of different parameters for instance, uncertainty of deterioration, and measurement errors can be tested. This study employs simulation research on a firm basis provided by prior empirical studies while at the same time enabling the generation of new knowledge regarding the improvement of M&R solutions [27].

Mathematical Framework

The mathematical basis of this research is based on time series analysis to capture the degradation of infrastructure facilities, the measurement errors and their effect on the decision of M&R [28]. This framework combines stochastic processes, state estimation, and cost minimization methods to give a holistic solution for managing infrastructure under uncertainty.

Deterioration Model

The degradation of the facility over a period is described by a discrete time stochastic process which is common among most papers on infrastructure management [29]. The state of the facility at time t is represented by X_t which is subject to the following Eq. (16).

$$`x_{t+1} = x_t + \epsilon_t - M_t \tag{21}$$

In this equation, x_t is the distress level of the facility at the start of period t; distress is expressed in terms of cracking measured in square feet. ϵ_t is the random deterioration shock which takes place in period t and is defined as a decentralized random variable with variance and mean equals to zero σ_ϵ^2. This shock expresses the stochastic nature of the deterioration process, which may be due to unpredictable events in the environment or fluctuations in the rates of material degradation. M_t is the total of the maintenance and repair actions carried out at time t which are assumed to enhance the condition of the facility thus reducing the degree of deterioration. The expected value of the facility's condition at $t + 1$ is calculated under the condition that no M&R actions are done, by using the following Eq. (17).

$$E[x_{t+1}|x_t] = x_t + E[\epsilon_t] = x_t \tag{22}$$

This value suggests that on average the condition of the facility would remain same in the absence of deterioration shocks, emphasizing the need to model stochastic changes in the deterioration process.

Measurement Error Model

The precision of the inspection technologies used to assess the facility's condition is modelled through a measurement error process. The observed measurement Y_t at time t is expressed as Eq. (18).

$$Y_t = x_t + \xi_t \tag{23}$$

where:

Y_t is the observed measurement of the state of the facility at t. ξ_t is the measurement error, assumed to be normally decentralized with variable and mean zero σ_ξ^2. The variance σ_ξ^2 reflects the precision of the measurement technology, with lower values indicating more accurate measurements. In cases where multiple inspection technologies are used, the correlation between the errors from different technologies is captured by a covariance matrix Σ_ξ. For two technologies, this matrix is defined as Eq. (19).

$$\Sigma_\xi = \begin{pmatrix} \sigma_{\xi_1}^2 & \rho_{12}\sigma_{\xi_1}\sigma_{\xi_2} \\ \rho_{12}\sigma_{\xi_1}\sigma_{\xi_2} & \sigma_{\xi_2}^2 \end{pmatrix} \tag{24}$$

Here, ρ_{12} represents the correlation coefficient between the measurement errors of the two technologies. A correlation of $\rho_{12} = 0$ indicates that the technologies are independent, while $\rho_{12} = 1$ suggests perfect correlation, meaning that the errors are completely dependent on each other. The use of a covariance matrix allows the model to account for the complex relationships between different measurement technologies and their impact on the accuracy of condition assessments.

Kalman Filter Implementation

To estimate the true state of the facility's condition x_t over time, given the noisy measurements Y_t, the Kalman filter is implemented as the primary state estimation technique. The Kalman filter is predominantly well-suited for this application because of its capacity to obtain optimal estimations in the presence of measurement noise and process uncertainty. The Kalman filter operates in two major phases: update and prediction. In the prediction phase, the filter projects the present state estimate forward in time based on the known model dynamics, in Eq. (20), and (21).

$$\hat{x}_{t+1|t} = \hat{x}_{t|t} + \hat{\epsilon}_t \tag{25}$$
$$P_{t+1|t} = P_{t|t} + \sigma_\epsilon^2 \tag{26}$$

Here, $\hat{x}_{t+1|t}$ is the forecasted condition at $t+1$ based on information available at time t, and $P_{t+1|t}$ is the predicted error covariance matrix, which accounts for the uncertainty in the prediction. In the update step, the filter incorporates the new measurement $Y_{t+1}$to refine the state estimate using Eq. (22), (23), and (24).

$$K_{t+1} = P_{t+1|t}\left(P_{t+1|t} + \sigma_\xi^2\right)^{-1} \tag{27}$$
$$\hat{x}_{t+1|t+1} = \hat{x}_{t+1|t} + K_{t+1}\left(Y_{t+1} - \hat{x}_{t+1|t}\right) \tag{28}$$
$$P_{t+1|t+1} = (I - K_{t+1})P_{t+1|t} \tag{29}$$

Here, K_{t+1} is the Kalman benefit that identifies the novel measurement relative to the prediction. The updated state estimate $\hat{X}_{t+1|t+1}$ incorporates the new measurement, providing a more accurate estimate of the facility's condition. The error covariance matrix $P_{t+1|t+1}$ is also updated, reflecting the reduced uncertainty after incorporating the measurement. The recursive nature of the Kalman filter makes it highly effective for continuous monitoring and decision-making in infrastructure management. By iteratively updating the state estimate as new data become available, the filter provides a robust tool for managing the uncertainty inherent in the deterioration and measurement processes.

IV. RESULTS AND DISCUSSION

Here, we provide numerical samples to demonstrate the manner in which inspection technology capabilities, whether multiple or simultaneous, are represented in the time series model. Additionally, we demonstrate how this model could be used to direct the choice of inspection innovations using economic parameters. More precisely, this research employs the time series model to:

- Investigate the influence of uncertainties, the processes of reduction and in the collection of information, on the most efficient expenses of controlling the facilities of transportation infrastructure;
- Evaluate the consequences of systematic measurements errors on the most effective decisions for maintenance and repair and the subsequent expenses of controlling the facilities of transportation infrastructure; and
- Establish the value of integrating inspection innovations for assessing the condition of transportation infrastructure facilities. We examine cases of facility management over an organization horizon of a hundred periods and make the assumptions that perioding cost functions, measurement-error model, and degradation model are represented by Eqs (25), (26), and (27), respectively.

$$g(X_t, A_t) = x_1^2 + A_t^2 - 700x_t + 121{,}597.75, \tag{30}$$
$$x_{t+1} = x_t - A_t + 30 + \epsilon_t; \text{where } \epsilon_t \infty N(0.\sigma_\epsilon^2), \quad t = 1, 2, \ldots, T \tag{31}$$
$$Z_t = x_t + \xi_t; \text{where } \xi_t \infty N\left(0, \sigma_\xi^2\right), \quad t = 1, 2, \ldots, T + 1 \tag{32}$$

The aforementioned settings were chosen to replicate simulations that align with the data used in the research conducted by [30], [31], and [32]. These studies examine several measurement systems for assessing alligator cracking on a collection of pavements that are currently in use. The salvage facility value is specified as ($s(X_{T+1}) = 0$), while rate of discount is set at 5% ($\delta = \frac{1}{1.05}$), and starting state, X_1, is set to 351, which represents its best long-term steady condition. For the simulations, we establish the Kalman filter by setting projections of the initial two periods of the conditional distribution $\mathbb{E}_{X_0|I_0}[X_0]$ and $V_{X_0|I_0}[X_0]$ to 350.5 and 10,000, respectively. In [33] and [34], the actual distress levels, derived from the measurements, varied between 200 and 500 square feet. We will presume that latent conditional variables are specified inside $y \equiv 200;\ y \equiv 500$ in the subsequent numerical examples.

The degradation process is such that, without maintenance and repair works, it could typically take facilities 10 rounds (periods) to go from its optimal state to its worst state [35]. The settings of the time expenditure function were selected to establish the long-term stable condition at y (midpoint) and to determine the ideal expenses for controlling a deterministic framework with flawless innovation to be \$0. The optimal selection of the beginning facility state and the plan horizon duration was made to minimize their influence on the outcomes. Before providing the findings of quantitative analysis, we highlight that our goal is to explore qualitative data on how modifications in parameters impact the optimum expenses of operating infrastructure assets. Therefore, the characteristics utilized in the research are not indicative of any specific facility, but the scenario examined was "stimulated" by pavement piece management that undergoes annual inspections to assess its state. Some factors, such as the duration of the review period, are determined by administrative choices in reality, while others may be predicted by time series analysis. An active research field is the formulation and estimate of degradation, user cost and measurement-error models, which are compatible with the model.

Uncertainty Impacts on Optimal Expenditure

Time series model is used to examine the uncertainty impact, including both the data-collection process and the degradation process, on the optimum costs associated with the management of infrastructure assets. Stochastic measurement errors related to the accuracy of a specific technology are a significant cause of uncertainty in the process of collecting data [36]. Thus, this work demonstrates how the suggested theoretical structure may be used to measure the worth of using inspection methods with varying levels of accuracy. Under this concept, the values σ_ϵ and σ_ξ represent uncertainties in the degradation and data-collection processes, correspondingly. In order to comprehend the implications of these factors on the expenses associated with infrastructure management, this study analyses their impact on optimal value of the objective functionality for the initial stage, $v_1(I_1)$. This value represents the lowest anticipated expenditure from the beginning of the initial time until the end of the planning period specified in I_1.

Firstly, it is important to observe that $v_1(I_1)$ exhibits a linear relationship with the variance of the degradation process, σ_ϵ^2 (refer to Eq. (6)). Measurement uncertainty, which is represented by σ_ξ, has a more nuanced impact on the data-collection process since it is not explicitly included in $v_1(I_1)$. From an intuitive standpoint, it is understood that this variable directly influences the state estimate variance, denoted as $\mathbb{V}_{X_1|I_1}(X_1)$. In other words, when the measurements are noisy, the estimation of the state becomes more uncertain. Considering the equation $\mathbb{E}_{X_1|I_1}[X_1^2] = \mathbb{V}_{X_1|I_1}(X_1) + \mathbb{E}_{X_1|I_1}^2[X_1]$ the ideal objective value function, $v_1(I_1)$, is shown to vary linearly with $\mathbb{V}_{X_1|I_1}(X_1)$. Regrettably, the impact of σ_ξ on $\mathbb{V}_{X_1|I_1}(X_1)$ can only be determined by experimentation (many iterations of the Kalman filter), since the impact is contingent upon the order of measurements, which in turn relies on $\sigma_\in$. Therefore, we performed simulation research using $\sigma_\in \in \{0, 2.5, 5, 7.5, 10\}$ and $\sigma_\xi \in \{0, 25, 50, 75, 100\}$ to further investigate the effects of r and r_n dynamics. In the simulation, the values of $\sigma_\in$ equals 0 and $\sigma_\in$ equals 10 represent a deterministic degradation and variable diminishment processes, correspondingly.

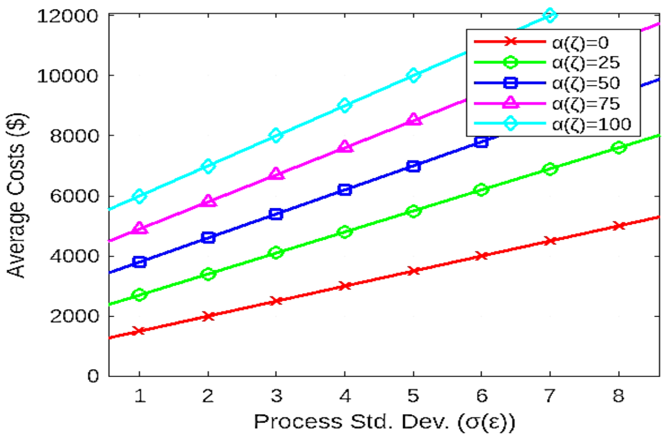

Fig 1. Deterioration Process SD Against Costs – Impacts of Technology Accuracy.

Equally, σ_ξ equals 0 denotes an ideal inspection innovation, while σ_ξ equals 100 denotes a very inaccurate technology. We conducted 1000 simulations of the degradation and inspection process outlined by Khakzad and Gholamian [37] for the remaining twenty-four set of the two variables, except the pair $(\sigma_\in, \sigma_\xi) = (0, 0)$. In **Fig 1**, the average total discounted costs of implementing the best maintenance and repair program are shown. **Fig 1** demonstrates that, as anticipated, the expenses for facility management rise with the amount of uncertainty in the degradation process.

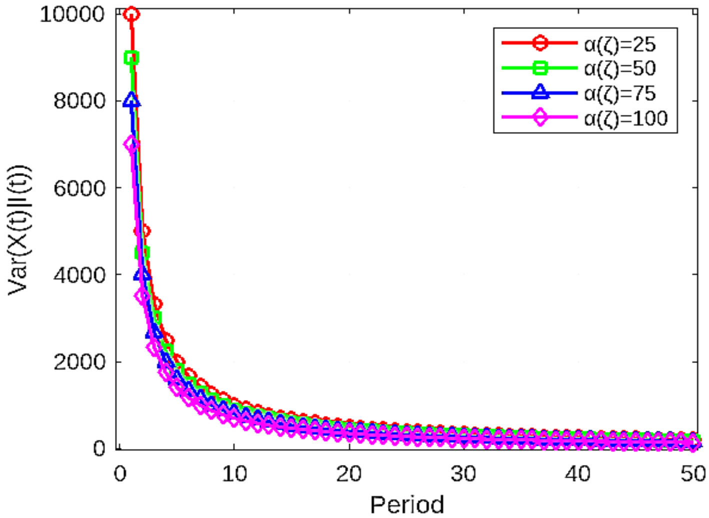

Fig 2. Upgraded State Distribution, As Second Moments

Additionally, it is evident that the use of inaccurate data collecting devices leads to higher costs. To evaluate the effects of σ_{ξ} on $\mathbb{V}_{X_t|I_t}(X_t)$ and values, we examine random examples of the simulations previously given with σ_{ϵ} being 5. **Fig 2** illustrates the process by which Kalman filter regulates the second period of state distribution for 4 mentioned innovations when $\sigma_{\xi}$is $25, 50, 75, 100$. We report a significant decrease in the variance of the state distribution over the early years. The convergence and asymptote rate are characteristics of the accuracy of a defined innovation. The use of precise technologies decreases the level of uncertainty in state distributions of X_t given I_t, resulting in a reduced value of $\mathbb{V}_{X_t|I_t}(X_t)$. This results in more effective and suitable maintenance and repair choices and leads to low costs during the planned period. An essential finding is that the state variance distributions fall comfortably within the accuracy of every innovation. This means that the method effectively eliminates any random noise or error in estimates. For instance, the variability in state distribution, when estimates are obtained using $\sigma_{\epsilon}^2 10,000$, becomes close to 1000.

Systematic Errors Impacts on Life-Cycle Expenses

Within this part, we examine the impact of errors, namely multiplicative and additive biases, on the most efficient costs of operationalizing infrastructure facilities. It should be noted that Measurement Upgrade phase in Kalman filter addresses the biases by adjusting the estimation of the initial two periods of state distributions for the ensemble of measurements [38, 39]. Previous research in the literature contended that if biases could be rectified, innovations with greater precisions (low values of σ_{ξ}) are more desirable [40, 41, 42]. Our analysis demonstrates that this assertion is not completely accurate since multiplicative biases alter the uncertainty level about distribution uncertainty of latent variables. Specifically, when considering a measurement-error framework, which characterizes the technology's capacity, the distribution variance of X_t may be expressed as $\frac{\sigma_{\xi}^2}{\beta}$.

In order to demonstrate the impact of multiplicative bias on the expenses associated with the management of infrastructure facilities, we examine specific cases of the process outlined in Eqs (8)– (10) with $\sigma_{\epsilon} \in \{0, 2.5, 5.0, 7.5, 10.0\}$. Given a description of the inspection technique with $\sigma_{\xi} = 50.0$ and $\beta \epsilon \{0.5, 1.0, 1.5, 2.0\}$, we conducted 1000 simulations for each of the 20 potential parameter combinations. **Fig 3** displays the average of the total discounted costs. Results demonstrate that technologies enabling more accurate estimations of the latent state, X_t, result in reduced life-cycle expenses.

Multiple Technology Integration Impacts for Condition Assessment

This section demonstrates the use of the time series model for quantifying the value of integrating various technologies. Furthermore, we demonstrate that the selection and implementation of inspection technologies should not be just based on accuracy, but should also take into account the interrelationship between various technologies and the data they generate. Our analysis focuses on an inspection procedure that produces two distress assessments, which serve as impartial metrics of the single-dimensional situation. Specifically, the measurement error framework may be defined in Eq. (28).

With a finite covariance matrix, a Gaussian distribution is assumed for the vectors ξ_t. Each technology is assumed to generate measurements with a high level of imprecision, with an error standard deviation of $\sigma_{\xi} = 50$. The correlation between the measures captures the connection between the technologies, and we analyze scenarios where $\rho = 0, 0.25, 0.5, 0.75, 1.0$ (where ρ is 0 indicates independent measurements/technologies and $\rho = 1$ indicates completely coupled technologies). The data shown in **Fig 4** pertain to the mean expenses collected from 1000 cases for each value of q. In addition, the number incorporates the mean expenses experienced whenever the facility is scrutinized by single technological advancement with σ_{ξ} is 50 and σ_{ξ} is 25. Observations indicate that when 2 or 3 independent technologies are used (q is 0), the expenses are comparable to those paid when a single form of technology where σ_{ξ} is 25 (i.e., an accurate technology) is used to monitor the facility.

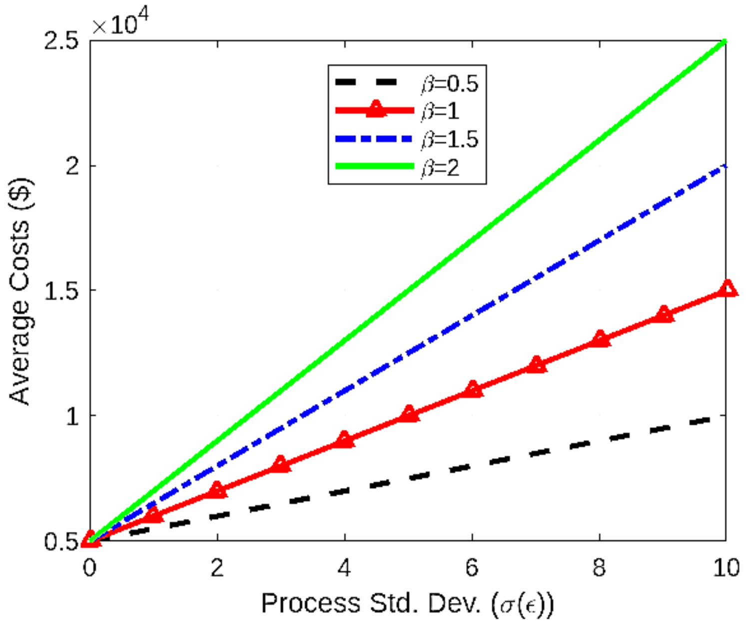

Fig 3. Deterioration Process SD Against Costs – Impact of Multiplicative Biases

$Z_t = x_t + \xi_t (33)$

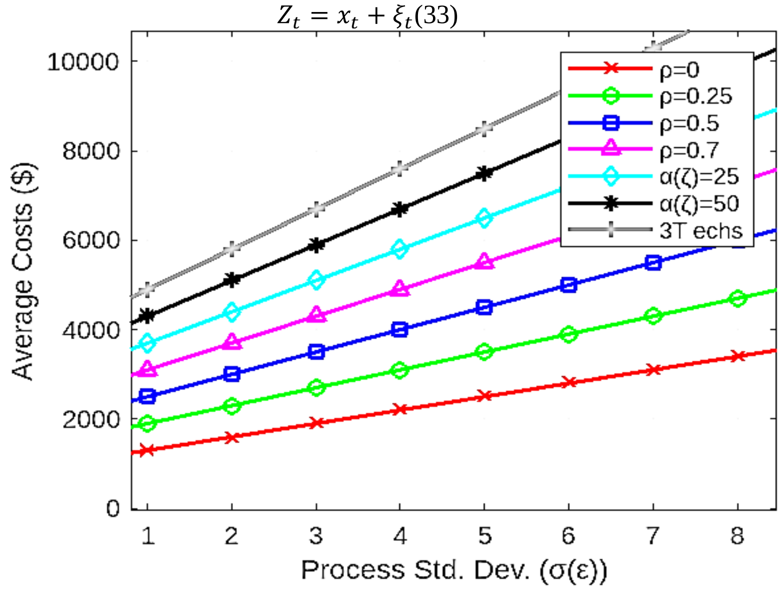

Fig 4. Deterioration Process SD Against Costs – Integrating Innovations for Conditional Measurements.

The inference is that the integration of inaccurate technologies may result in significant cost reductions [43]. This is crucial since technically advanced technologies with great precision tend to incur substantially higher costs for implementation [44], especially when they are initially introduced. In instances where the measurements exhibit perfect correlation ($\rho = 1$), the expenses are directly equivalent to the expenditures incurred whenever facility is operated using technologies where σ_ξ is 50. In this scenario, the collection of a second or further distress measures does not provide any more information.

V. CONCLUSION AND FUTURE SCOPE

The integration of time series analysis into infrastructure management substantially raises the accuracy of deterioration pattern prediction and optimizes the maintenance and repair strategies. This paper proves that through the use of historical data and evidence of variance in measurement precision, time series models could be employed to predict future conditions of infrastructure and thereby enable more timely and cheaper interventions to be made. The findings suggest that implementing this strategy also decreases the likelihood of failures that are disruptive while at the same time improving the efficiency in the use of resources so that, in the long run, considerable cost savings and reliability of infrastructural systems are realized. In addition, the application of uncertainty quantification in the processes of decision-making leads to a more effective approach in dealing with the aging infrastructure, while the maintenance and repair activities are timely and more effective. In general, this paper establishes the importance of the use of high-level data analysis in current infrastructure planning and creates a platform for subsequent research, which will seek to improve the current approaches to efficient maintenance.

CRediT Author Statement
The authors confirm contribution to the paper as follows:
Conceptualization: Zheng Xinyu and He Xin; **Methodology:** Zheng Xinyu; **Writing- Original Draft Preparation:** He Xin; **Validation:** Zheng Xinyu and He Xin; **Writing- Reviewing and Editing:** Zheng Xinyu and He Xin; All authors reviewed the results and approved the final version of the manuscript.

Data Availability
The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests
The authors declare that they have no conflicts of interest regarding the publication of this paper.

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Competing Interests
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