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# Effect of Inspection Errors in Optimal Maintenance Decisions for Deteriorating Quoin Blocks in Miter Gates

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## ABSTRACT

Condition-based maintenance (CBM) is a modern maintenance approach that combines data-driven reliability models and information from a condition monitoring process (e.g. inspections and continuous monitoring). Maintenance schedules are predicted based on the results from diagnosis and prognosis. Due to aging in its infrastructure, the US Army Corps of Engineers (USACE) has equipped some of their navigation infrastructure with sensors to allow continuous monitoring. Miter gates are one of the most important such structural assets because of their economic impact on navigation corridor. Miter gates prognosis and maintenance schedule capabilities can be improved when a discrete-state deterioration model based on inspection data is used. One of the sources of inspection data available for miter gates are the operational condition assessment (OCA) discrete ratings. However, these discrete ratings are highly abstracted, assigned at variable frequencies, and are very prone to human error and to misinterpretations due to inspection protocols. In miter gates, OCA ratings are available for deteriorating components such as quoin blocks. Over time, contact between these quoin blocks deteriorates, ultimately leading to failure, which can be generally avoided with timely maintenance schedules. To overcome these issues, this paper proposes a structural health monitoring-based CBM framework that accounts for different levels of human observation errors in the inspection data. This proposed framework shows (1) how to use physics-informed (e.g. finite element) simulations to perform damage diagnosis in miter gates and (2) how to account for human observation errors to improve prognosis and maintenance schedule capabilities for deteriorating components (e.g. quoin blocks) in miter gates.

**Keywords:** Miter Gates, Uncertainty Quantification, Model updating, Prognosis and Health Management.

## INTRODUCTION

Miter gates are hydraulic steel structures that are considered the most common type of lock gate. The purpose of miter gates is to allow passage of ships, boats, and watercraft through between various water elevation levels in navigation system in rivers. In the United States, the U.S. Army Corps of Engineers (USACE) maintains and operates 236 locks at 191 sites [1]. A closure of a lock due to maintenance or repairs can cost up to \$3 million per day to the US economy [2]. More than half of these structural assets, including miter gates, have surpassed their 50-year economic design life [3]. To help prioritizing maintenance and repairs, operational condition assessment (OCA) ratings have been performed by USACE inspectors via visual inspections [4]. However, the OCA ratings are highly abstracted and are assigned at a varying frequency, which varies from every year to occurring to a maximum of every 5 years. Recently, many miter gates are equipped with SHM systems which can collect strain measurement data in real time [5]. These continuous monitoring systems aims to provide insight regarding deteriorating gates. A framework that integrates visual inspections accounting for human discrepancies and SHM for damage diagnosis and prognosis have been developed and presented in this work.

## REPORTED OCA TRANSITION MATRIX TO TRUE OCA TRANSITION MATRIX

Based on a large historical OCA database, the number of times that a component transitioned from one rating category to another (as determined by engineering expert elicitation) over a given inspection time step can be determined to generate the rating transition matrix. The transition matrix  $\mathbf{P}$  (see Eq. (1)) is defined as a square matrix with nonnegative values that

represents how some process “transitions” from one state to the next. In this application, an inspected state at time  $t$ ,  $I_{t,t}$ , (with  $i = 1 \dots 6$ , corresponding to the 6 letter ratings specified above), will transition to inspected state at time  $t+1$ ,  $I_{j,t+1}$ ,  $j = 1 \dots 6$ , according to

$$\mathbf{P}_{\text{Report}} = P(\mathbf{I}_{t+1}^{obs} | \mathbf{I}_t^{obs}) = \begin{bmatrix} P(A_{t+1}^R | A_t^R) & \dots & P(CF_{t+1}^R | A_t^R) \\ \vdots & \ddots & \vdots \\ P(A_{t+1}^R | CF_t^R) & \dots & P(CF_{t+1}^R | CF_t^R) \end{bmatrix}, \quad (1)$$

In order to map the reported OCA rating transition matrix to the underlying “true” OCA transition matrix, the underlying true OCA rating is defined at time  $t$  as  $I_t^{tr}$  and that at  $t+1$  as  $I_{t+1}^{tr}$ , the reported OCA rating from field engineers at time  $t$  as  $I_t^{obs}$  and that at time  $t+1$  as  $I_{t+1}^{obs}$  as shown in Figure 1.

$$\Pr\{I_t^{obs} = k | I_t^{tr} = i\} = P_{ik}^h, \forall i = 1, 2, \dots, 6; k = 1, 2, \dots, 6;$$

$$\Pr\{I_{t+1}^{obs} = q | I_{t+1}^{tr} = j\} = P_{jq}^h, \forall j = 1, 2, \dots, 6; q = 1, 2, \dots, 6;$$

$$\Pr\{I_{t+1}^{obs} = q | I_t^{obs} = k\} = P_{kq}^R, \forall k = 1, 2, \dots, 6; q = k, \dots, 6$$

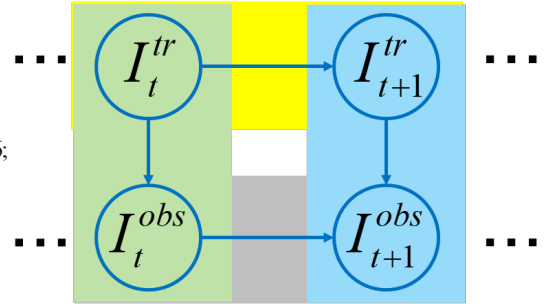
$$\Pr\{I_{t+1}^{obs} = q | (I_{t+1}^{tr} = j, I_t^{obs} = k)\} = P_{kq}^R, \forall j = 1, 2, \dots, 6; k = 1, 2, \dots, 6; q = 1, 2, \dots, 6;$$

$$\Pr\{I_{t+1}^{tr} = j | I_t^{tr} = i\} = P_{ij}^h, \forall i = 1, 2, \dots, 6; j = i, \dots, 6$$

$$P_{kq}^R \Pr\{I_t^{obs} = k\}$$

$$= \sum_{i=1}^6 \sum_{j=1}^6 \left( \frac{P_{kq}^R \Pr\{I_t^{obs} = k\} P_{jq}^h \Pr\{I_{t+1}^{tr} = j\}}{\Pr\{I_{t+1}^{obs} = q\}} \right) P_{ik}^h \Pr\{I_{t+1}^{tr} = j | I_t^{tr} = i\} \Pr\{I_t^{tr} = i\}.$$

Solved by constrained least-squares method  
(probability estimates are in the range of [0, 1])



A Bayesian network connecting the observed and the true OCA ratings

$$\mathbf{P}_{\text{OCA}} = \begin{bmatrix} P_{11}^{OCA} & P_{12}^{OCA} & \dots & P_{16}^{OCA} \\ 0 & P_{22}^{OCA} & \dots & P_{26}^{OCA} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & P_{66}^{OCA} \end{bmatrix},$$

Fig. 1: Mapping between reported OCA transition matrix to compensated/true OCA transition matrix

As shown in Figure 1, to map  $\mathbf{P}_{\text{Report}}$  to  $\mathbf{P}_{\text{OCA}}$ , the human observation error matrix needs to be obtained/estimated as follows

$$\mathbf{P}_{\text{human}} = \begin{bmatrix} P_{11}^h & P_{12}^h & \dots & P_{16}^h \\ P_{21}^h & P_{22}^h & \dots & P_{26}^h \\ \vdots & \vdots & \ddots & \vdots \\ P_{61}^h & P_{62}^h & \dots & P_{66}^h \end{bmatrix} \xrightarrow{\text{Assume}} \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0.04 & 0.96 & 0 & 0 & 0 & 0 \\ 0 & 0.40 & 0.60 & 0 & 0 & 0 \\ 0 & 0.03 & 0.17 & 0.80 & 0 & 0 \\ 0 & 0 & 0 & 0.03 & 0.97 & 0 \\ 0 & 0 & 0 & 0 & 0.03 & 0.97 \end{bmatrix}, \quad (2)$$

in which  $P_{ik}^h = \Pr\{I_t^{obs} = k | I_t^{tr} = i\}$  is the probability that the reported OCA rating is  $k$  given that the true OCA rating is  $i$ .

Now, the assumed  $\mathbf{P}_{\text{human}}$  represents the behavior of an inspector that regularly tends to assess a structural component to be in a better condition than reality.

## FRAMEWORK AND RESULTS

As shown in this Figure 2, the proposed framework first estimates the damage state (i.e. gap length) using online SHM data using sequential updating. After that, the estimated gap length is mapped from its continuous state to its corresponding gap (OCA rating) state. The current state at time “n” with the true OCA transition matrix are used to estimate the rating state at time “n+m”, which can be used to estimate the probability of failure and the remaining useful life at this time step as denoted in Figure 2. This framework is categorized as a hybrid approach because it uses a physics (FE) based model for diagnosis and a data driven model (the Transition Matrix) for prognosis.

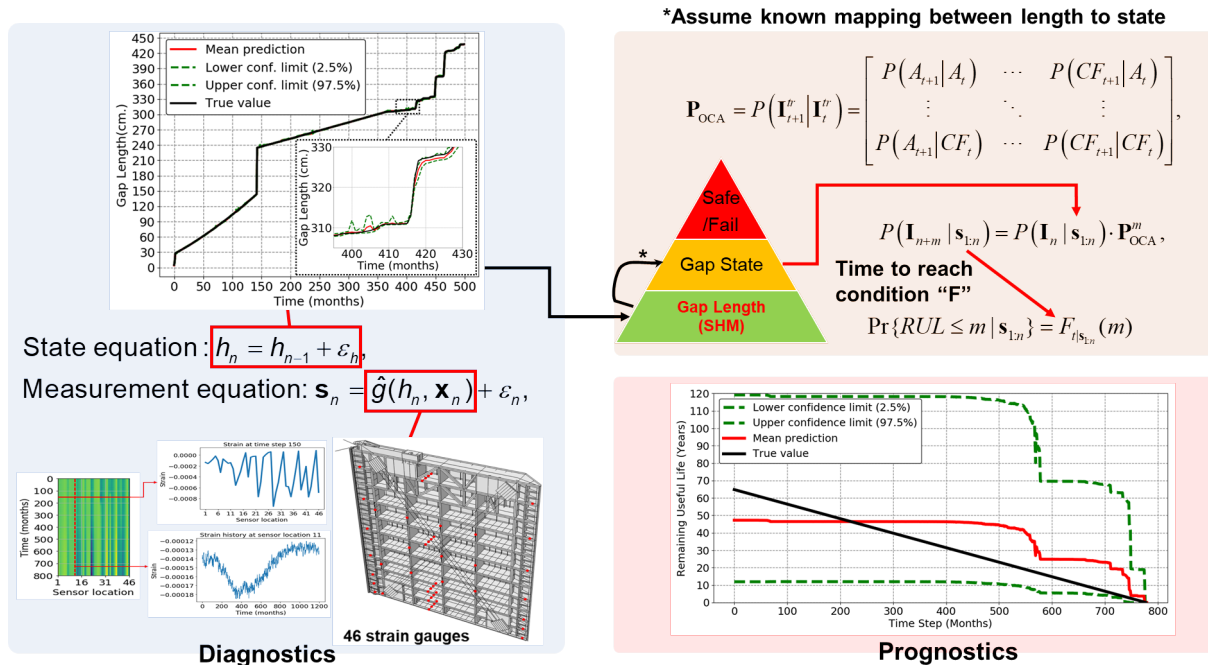


Fig. 2: Diagnosis and Prognosis of gap lengths in miter gates using compensated OCA ratings and SHM systems

## CONCLUSION

This work proposed a new hybrid CBM approach that integrates high-fidelity FE model-based SHM with inspection data based transition matrix for effective diagnosis, prognosis, which includes quantification of effects of uncertainty in OCA ratings. Results capture correctly the true gap length and the true remaining useful life of the quoin blocks assuming its only deterioration mechanism is the formation of a bearing gap.

## ACKNOWLEDGEMENTS

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